

UNIVERSIDAD DE SALAMANCA

Departamento de Ingeniería Cartográfica y del Terreno



TESIS DOCTORAL

MENCIÓN INTERNACIONAL

**Fotogrametría de rango cercano aplicada
a la Ingeniería Agroforestal**

Mónica Herrero Huerta

Directores de Tesis:

Dr. Diego González Aguilera

Dr. David Hernández López

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Departamento de Ingeniería Cartográfica y del Terreno
Escuela Politécnica Superior de Ávila
Universidad de Salamanca

AUTORA:

Mónica Herrero Huerta

DIRECTORES:

Dr. Diego González Aguilera

Dr. David Hernández López

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La presente Tesis Doctoral corresponde a un compendio de tres artículos científicos previamente publicados en revistas internacionales de impacto y que se especifican a continuación:

1. Vicarious Radiometric Calibration of a Multispectral Sensor from an Aerial Trike Applied to Precision Agriculture

Mónica Herrero-Huerta¹, David Hernández-López², Pablo Rodríguez-Gonzálvez¹, Diego González-Aguilera¹, José González-Piqueras²

¹Department of Cartographic and Land Engineering, University of Salamanca, Higher Polytechnic School of Avila, Hornos Caleros 50, 05003, Avila, Spain.

²Institute for Regional Development (IDR), University of Castilla La Mancha, 02071, Albacete, Spain

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2. Vineyard Yield Estimation by Automatic 3D Bunch Modelling in Field Conditions

Mónica Herrero-Huerta¹, Diego González-Aguilera¹, Pablo Rodríguez-Gonzálvez¹, David Hernández-López²

¹Department of Cartographic and Land Engineering, University of Salamanca, Higher Polytechnic School of Avila, Hornos Caleros 50, 05003, Avila, Spain.

²Institute for Regional Development (IDR), University of Castilla La Mancha, 02071, Albacete, Spain

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3. Dense Canopy Height Model from a low-cost photogrammetric platform and LiDAR data

Mónica Herrero-Huerta¹, Beatriz Felipe-García², Soledad Belmar-Lizarán², David Hernández-López², Pablo Rodríguez-Gonzálvez¹, Diego González-Aguilera¹

¹Department of Cartographic and Land Engineering, University of Salamanca, Higher Polytechnic School of Avila, Hornos Caleros 50, 05003, Avila, Spain.

²Institute for Regional Development (IDR), University of Castilla La Mancha, 02071, Albacete, Spain

Trees

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Al Somormujo Lavanco, página 8, “En el estanque”

*«No es la más fuerte de las especies la que sobrevive y tampoco la más inteligente.
Sobrevive aquella que más se adapta al cambio»*

(Charles Darwin)

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RESUMEN

Desde finales del siglo XX se están aplicando Geotecnologías en diferentes líneas de investigación en Ingeniería Agroforestal orientadas a avanzar en la modelización de parámetros biofísicos con el propósito de mejorar la productividad. En este estudio se ha empleado fotogrametría de bajo coste y rango cercano en distintos escenarios agroforestales para solventar carencias detectadas en los resultados obtenidos y mejorar los procedimientos y la tecnología hasta ahora usados en este campo. La fotogrametría ofrece como ventaja el ser una técnica no invasiva y no destructiva, por lo que no altera en ningún momento las propiedades físicas del elemento estudiado, dotando de rigor y exhaustividad a la información capturada.

En esta Tesis Doctoral se presentan las siguientes contribuciones, divididas en tres artículos de investigación:

- Una propuesta metodológica de adquisición de datos multiespectrales georreferenciados de alta resolución espacial mediante una plataforma aérea tripulada de bajo coste, para monitorizar y gestionar sosteniblemente amplias extensiones de cultivos.

Se expone la calibración vicaria como método de calibración radiométrico del sensor multiespectral embarcado en un paramotor empleando como coberturas de control superficies de bajo coste.

- El desarrollo de un método capaz de determinar la productividad del cultivo en condiciones de campo, a partir de la combinación de fotogrametría de rango cercano y visión computacional, facilitando una mejora operativa constante así como una gestión proactiva en la monitorización del cultivo.

Se propone una metodología totalmente novedosa en el sector, garantizando flexibilidad y sencillez en la toma de datos mediante tecnologías no invasivas, automatismo en el procesado, calidad en los resultados y un bajo coste asociado.

- Una metodología de bajo coste, eficiente y precisa para la obtención de Modelos Digitales de Altura de Cubierta Vegetal destinados al inventario forestal mediante la integración de datos públicos procedentes del LiDAR en las nubes de puntos fotogramétricas obtenidas con un vuelo de bajo coste.

Esta metodología engloba la potencialidad del LiDAR para registrar el terreno en zonas con alta densidad de vegetación y una mejor resolución espacial, radiométrica y temporal procedente de la fotogrametría para la parte superior de las cubiertas vegetales.

Palabras clave: calibración vicaria, sensor multiespectral, plataforma de bajo coste, reflectancia, fotogrametría, visión computacional, automatización, tecnologías no invasivas, modelo digital de altura de cubierta vegetal, fusión de datos, LiDAR, segmentación radiométrica.

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I. INTRODUCCIÓN

1. INTRODUCCIÓN

Desde la última década del siglo XX se vienen desarrollando líneas de investigación sobre la aplicabilidad de Geotecnologías a la Ingeniería Agroforestal, con el fin de optimizar la gestión agroforestal, medioambiental y económica. En esta Tesis Doctoral se realizan aportaciones que avanzan en la dirección de la aplicación de metodologías derivadas de la fotogrametría de bajo coste y rango cercano aplicadas a este campo, que ponen a disposición del individuo numerosa información referente a la monitorización del campo, ayudas a la toma de decisiones y necesidades de trazabilidad y una mejora de la calidad intrínseca de los productos agrícolas y forestales obtenidos.

Se han planteado tres casos de estudio, generando una continuidad en la investigación que conforma la presente Tesis Doctoral:

- Fotogrametría multiespectral aérea para análisis agronómicos: fotogrametría de bajo coste y rango cercano mediante paramotor de grandes extensiones de cultivos. El rango espectral del estudio se encuentra entre el espectro visible e infrarrojo cercano (NIR), rango óptimo para estudios vegetales que posibilita la obtención de índices vegetales. La aportación en esta línea de investigación se centra en uno de los primeros problemas a resolver en el empleo de cámaras multiespectrales embarcadas en plataformas aéreas, la calibración radiométrica de los sensores que permita obtener magnitudes físicas a partir de los niveles digitales almacenados en las imágenes. Se pretende a su vez avanzar en la convergencia entre fotogrametría y teledetección.
- Fotogrametría terrestre para estimar la producción agronómica: fotogrametría de bajo coste y rango cercano mediante cámaras digitales compactas y reflex. La contribución a esta línea de investigación aborda la problemática que supone la imprecisión en la predicción del cultivo con suficiente antelación para una correcta planificación de la cosecha. El experimento se lleva a cabo en un viñedo y se estiman las variables de volumen, peso y número de bayas asociadas a cada racimo.

- Fotogrametría aérea para la gestión forestal: fotogrametría de bajo coste y rango cercano mediante paramotor de una gran extensión de bosque con aplicaciones al inventario forestal. La aportación en esta línea de investigación se orienta a desarrollar una metodología que permita aplicar al inventario forestal la combinación de fotogrametría aérea de bajo coste y datos LiDAR existentes. Así se posibilita la explotación de las ventajas de ambas técnicas: por un lado se extrae información LiDAR del terreno constante en el tiempo, y por el otro se consigue la modelización de la cubierta vegetal en el momento necesario dado el bajo coste que ofrece la fotogrametría. El caso estudiado se trata de un área de *pinus nigra*.

A continuación se realiza un breve recorrido introductorio a través de las diferentes aplicaciones de la fotogrametría de rango cercano llevadas a cabo.

1.1. Fotogrametría multiespectral de bajo coste para análisis agronómicos

La posibilidad de embarcar cámaras multiespectrales en plataformas aéreas tripuladas de bajo coste tipo paramotor, permite realizar estudios radiométricos de gran precisión aplicables a la agricultura con la resolución temporal requerida. La base de estos estudios radica en que la curva de reflectancia de un cultivo está directamente relacionada con sus características fenológicas, fisiológicas y morfológicas, por lo que cualquier cambio en la planta también perturbará su reflectancia y por ende, su radiometría (Lass y Callihan, 1997; Schmidt y Skidmore, 2003). Estas diferencias de comportamiento espectral intrínseco de cada especie son las que permiten su discriminación y mapeo mediante técnicas de análisis y clasificación digital. Para ello, el sensor de captura ha de someterse a una calibración en la que se analice el comportamiento radiométrico de cada píxel en las distintas regiones del espectro electromagnético en el que se ha registrado la información, usando como verdad terreno la radiancia obtenida en distintas superficies con el espectralradiómetro calibrado (Honkavaara et al., 2009). En este estudio se propone un método de calibración vicario que tiene como novedad además de la plataforma aérea alternativa utilizada, el empleo de superficies de control de bajo coste que dotan al modelo matemático de numerosos puntos de ajuste. La altura de vuelo implica la presencia de una capa atmosférica que obliga a incluir el estudio de su efecto sobre la

relación entre la radiación recibida en el sensor frente reflejada desde la cubierta observada, por lo que se establece un modelo de transferencia radiativa.

El uso del paramotor como plataforma de vuelo ofrece múltiples ventajas, como la capacidad de adquirir datos de alta resolución espacial, espectral y temporal con un bajo coste asociado y gran capacidad de carga, propiedades que lo definen como tecnología idónea para aplicaciones agronómicas. Además, el progreso de la microelectrónica en el campo de los equipos de navegación (GNSS/IMU-Global Navigation Satellite System/Inertial Measurement Unit), ha permitido dotar a estas plataformas tripuladas de bajo coste de una solución de calidad para determinar la posición espacial y angular del sensor o sensores y por ende de su trayectoria. Todo ello posibilita una adecuada planificación y ejecución del vuelo del paramotor para conseguir los objetivos previamente definidos de cada campaña, permitiendo mejores resoluciones temporales que las obtenidas con la planificación de vuelos clásicos fotogramétricos (Hernández et al., 2013).

La fotogrametría multiespectral de rango cercano ha ido cobrando mayor importancia en los estudios de análisis de la vegetación debido a las ventajas que este tipo de técnicas ofrecen por el hecho de no ser destructivas ni invasivas (Zhang y Kovacs, 2012), provocando una convergencia con la teledetección. Existen numerosos estudios desarrollados sobre plataformas aéreas convencionales y satelitales de imágenes multiespectrales e hiperespectrales en la evaluación de cultivos (Herwitz et al., 2004; Chen et al., 2006; Zarco-Tejada, 2004). Incluso son varios los autores que han publicado trabajos en los que usando cámaras multiespectrales, térmicas u otras convencionales en pequeños aviones o helicópteros no tripulados, han demostrado su viabilidad como plataformas para la adquisición de imágenes para estudios vegetales (Esposito, 2007; Xiang y Tian, 2007; Turner et al., 2011; Zhao et al., 2006). Sin embargo, no existen estudios hasta el momento en los que plataformas tripuladas de bajo coste del tipo paramotor hayan sido utilizadas para realizar la monitorización de cultivos, siendo una plataforma de bajo coste tripulada idónea para el estudio de grandes extensiones de cultivo debido a los requerimientos ya mencionados.

El propósito de este estudio es verificar una nueva metodología de adquisición de datos multiespectrales georreferenciados de alta resolución espacial tras calibrar

radiométricamente el sensor multiespectral, para monitorizar cultivos y poder determinar zonas con patologías o deficiencias hídricas y nutricionales, analizando dicha metodología en un área cultivada de 5,4 hectáreas mediante un vuelo de diferentes alturas en una plataforma tripulada tipo paramotor y usando en todo momento herramientas de código abierto.

1.2. Estimación del rendimiento de viñedos

El desarrollo de las tecnologías innovadoras en viticultura para monitorizar viñedos y obtener uva de alta calidad a unos costes de producción sostenibles, se fomenta debido a su gran impacto ambiental y económico de la sociedad. Una de las principales preocupaciones del sector vitivinícola a lo largo de la historia ha sido la estimación precisa y objetiva del rendimiento productivo y potencial enológico del viñedo, “crop forecasting” o pronóstico de cosecha. Este es un tema aún no resuelto en la actualidad y de gran importancia técnica y económica (Wolpert y Vilas, 1992; Clingeleffer et al., 2001; Dunn y Martin, 2004). Una buena predicción del rendimiento del viñedo permite obtener unos viñedos más eficientes y establecer su potencial cualitativo, produciendo vinos de mayor calidad (Dunn y Martin, 2003).

Actualmente, los métodos aplicados a escala industrial para estimar la productividad del viñedo son métodos manuales y destructivos (Martin et al., 2003), y por lo tanto, económicamente poco viables. Asimismo se han desarrollado métodos basados mayoritariamente en una inspección ocular del viñedo, no garantizando datos fiables ni rigurosos o mediante costosas mediciones (Blom y Tarara, 2009; Serrano et al., 2012). Es por ello que en los últimos años se ha comenzado a aplicar el análisis de imagen en viticultura, tratando de evaluar el estado vegetativo o el rendimiento del viñedo (Dunn y Martin, 2004; Nuske et al., 2011); incluso técnicas 2D de visión computacional han sido aplicadas en cepas individuales para la identificación de los elementos que conforman las plantas (Herrero-Langreo et al., 2010; Diago et al., 2012) o deparar un conteo individual de bayas utilizando sistemas láser escáner (Battany, 2008). Acercamientos sobre la obtención de modelos 3D a partir de fotografías para análisis de plantas se ha llevado a cabo en laboratorio en plantas individuales de tomate (Aguilar et al., 1998) sin conseguir una automatización efectiva ni transpasar esta tecnología a condiciones de campo.

Con este trabajo se pretende establecer un método de estimación de la producción vitícola en condiciones de campo mediante métodos de bajo coste y no invasivos basados en la fotogrametría de rango cercano y la visión computacional (Sethian, 1999) para conseguir modelos 3D del racimo a partir de los cuales poder establecer un análisis dimensional y hallar las diferentes componentes de rendimiento. El desarrollo del método propuesto, cuenta con la dificultad de que la documentación in-situ de los racimos genera modelos 3D parciales (sólo la cara visible del racimo), así como el tener que hacer frente a las oclusiones y complejidades geométricas propias de la cepa, sin olvidar las propias condiciones de iluminación de la escena, siempre complejas. Esto supone un reto añadido y totalmente innovador a la hora de derivar variables con respecto a la totalidad del racimo, desarrollando técnicas y algoritmos de cálculo para la estimación de las componentes de producción del viñedo. Gracias al uso de diferentes técnicas, basadas en geometría computacional, se consigue la reconstrucción de la parte oculta mediante envolventes convexas (Barber et al., 1996).

Este estudio muestra un método preciso de estimación de la productividad del viñedo que permitirá al viticultor la toma de decisiones con suficiente antelación para evitar diferencias ostensibles entre campañas o incluso dentro de una misma parcela. Se pretende con ello minimizar la subjetividad derivada de la variabilidad espacial y temporal en cifras de rendimientos de producción de uva por unidad de superficie y del potencial enológico de bayas entre diferentes añadas.

1.3. LiDAR y fotogrametría aplicadas a la gestión forestal

La estimación de las variables dasométricas de interés para la gestión de masas forestales (diámetro, altura, área basal, volumen, biomasa, especie) ha sido tradicionalmente realizada con inventarios de campo a través de muestreos piloto. Con la introducción de las nuevas tecnologías teledetección y fotogrametría se abre un campo de posibilidades para la ejecución de estos trabajos, que proporciona ventajas respecto al coste económico, tiempo invertido y error de estimación.

La aplicación de sensores remotos activos de alta resolución permite una elevada precisión en las mediciones en altura y buena predicción de variables dasométricas. Concretamente, la capacidad de los sensores activos LiDAR (Light Detection and

Ranging) para penetrar y adquirir medidas tridimensionales de la cubierta arbórea a diferentes alturas (Wulder et al., 2013) permite mejorar la estimación de variables como la biomasa, el volumen o el área basimétrica, respecto a otros sensores de medida bidimensional, como los sistemas fotográficos o los radiómetros.

En los últimos años, se han publicado muchos estudios y revisiones metodológicas que ponen de manifiesto la operatividad e implantación definitiva de la tecnología LiDAR en el ámbito de la extracción de variables forestales (Hyypä et al., 2008; Kankare et al., 2013; Wulder et al., 2012). Benko y Balenovic (2011) aportan nuevas experiencias en las labores de inventario y gestión forestal en distintos ámbitos con análisis de las precisiones. Richardson y Moskal (2011) establecen clasificaciones de la vegetación a través de la altura de los árboles y densidad. Asimismo, cabe destacar la guía presentada por el Servicio Forestal de Canadá como documento de referencia actual realizado en base a todas las experiencias publicadas con anterioridad, que establece una serie de recomendaciones en las aplicaciones forestales de inventario basados en los métodos de rodal realizados a partir de LiDAR (White et al., 2013a). Por su parte, Gleason e Im (2012) aplican diferentes acercamientos de aprendizaje automático para estimar la biomasa en bosques a partir de datos LiDAR aéreos. Los sistemas LiDAR aerotransportados de onda completa (FullWave) son una tecnología que extrae gran cantidad de información de toda la estructura vegetal y forestal en detalle (Mallet y Bretar, 2009; Weinacker et al., 2004). Como desventajas destaca su procesamiento complejo y tedioso, así como el coste que implica dicha tecnología (Chauve et al., 2007; Gupta et al., 2010).

En España, en el marco del Plan Nacional de Ortofotografía Aérea, se han realizado vuelos con sensores LiDAR de baja densidad (0.5 puntos/m²) desde 2008 en todo el territorio. De este modo, en los últimos años distintos grupos de investigación forestal han realizado diferentes aplicaciones con esta fuente de información (Estornell et al., 2012; Gonzalez-Ferreiro et al., 2014; Navarro-Cerrillo et al., 2014). El problema de estas capturas masivas de información es que son costosas, de baja resolución y se producen de forma puntual en un instante determinado, obligando a usar modelos de predicción del crecimiento de las masas forestales.

En la actualidad, la fotogrametría digital moderna es una alternativa complementaria a los vuelos específicos LiDAR para obtener nubes de puntos 3D y modelos digitales de

superficie (MDS) ya que tiene un menor coste asociado (Järnstedt et al., 2012), mayor precisión y mayor resolución espacial, radiométrica y temporal (Bohlin et al., 2012). La complementariedad de ambas técnicas desde un punto de vista fotogramétrico, se remarca en la mayor precisión planimétrica de la fotogrametría frente al LiDAR y de la mejor precisión altimétrica de éste frente a la fotogramétrica. No obstante, la fotogrametría muestra la imposibilidad de generar un modelo digital del terreno (MDT) bajo las zonas cubiertas por vegetación, recurriendo a información LiDAR para la generación de superficies de referencia y con ello la obtención de alturas de vegetación (Järnstedt et al., 2012). En White et al., (2013b) citan como ventaja de la nube de puntos fotogramétrica el hecho de poder interpretar la composición de especies, la madurez y la salud de la vegetación.

Con el desarrollo de nuevas plataformas aéreas de bajo coste tripuladas y no tripuladas (RPAS-Remotely Piloted Aircraft Systems), se permite llevar a cabo el flujo fotogramétrico convencional. En Tao et al., (2011) emplean nubes densas de puntos fotogramétricas obtenidas mediante RPAS en zonas forestales, consiguiendo información de densidad de vegetación, composición o cambios en la cubierta forestal. Otros autores (Wallace et al., 2012; Jaakkola et al., 2010) combinan cámaras y sistemas LiDAR ligeros en plataformas no tripuladas permitiéndoles trabajar simultáneamente con ambos sensores. Para finalizar, hay que destacar el estudio realizado por Lisein et al., (2013) en el que se obtiene un modelo digital de altura de cubierta vegetal de carácter híbrido, combinando el MDS de vegetación obtenido mediante técnicas de correlación de imágenes procedentes de cámara no métrica y RPAS con un MDT obtenido a partir de datos LiDAR para estimar diferentes parámetros forestales.

Este estudio propone una metodología para generar Modelos Digitales de Altura de Cubierta Vegetal basado en el registro de nubes de puntos procedentes de datos públicos LiDAR y del flujo de trabajo fotogramétrico de un vuelo de bajo coste. Con el fin de minimizar los errores de georreferenciación de ambas fuentes, los datos del terreno LiDAR se refinan para ser incluidos en la nube de puntos fotogramétrica a través de un modelo de corrección basado en un análisis estadístico de alturas. Como resultado, se obtiene una nube de puntos a partir de la fusión, que engloba la potencialidad del LiDAR para alcanzar el terreno en esas áreas con vegetación alta y la mayor resolución espacial, radiométrica y temporal procedente de la fotogrametría. La nube de puntos resultante, a

través de un proceso de segmentación radiométrica y geométrica, permite generar un Modelo Digital de Altura de Cubierta Vegetal para aplicaciones de gestión forestal.

II. HIPÓTESIS DE TRABAJO Y OBJETIVOS

2. HIPÓTESIS DE TRABAJO Y OBJETIVOS

2.1. Hipótesis

Tras una introducción en la que se muestra una visión general de la aplicación de la fotogrametría de bajo coste y rango cercano a la Ingeniería Agroforestal, se plantean una serie de hipótesis que pretenden verificar las metodologías propuestas:

- La incorporación de la fotogrametría aérea de bajo coste y rango cercano multiespectral (visible y NIR) al campo agroforestal es una técnica excelente para la obtención de información georreferenciada y métrica con la resolución temporal, espacial y espectral requerida.
- Por medio de la fotogrametría terrestre de bajo coste y rango cercano y algoritmos de visión computacional es posible estimar la producción del cultivo, concretamente viñedos, en condiciones de campo y de manera semi-automática, modelando métricamente escenarios agronómicos complejos.
- Mediante la combinación de fotogrametría aérea de bajo coste y rango cercano con datos públicos LiDAR de diferente resolución temporal es posible generar documentación aplicable a la gestión forestal en el área y momento adecuado de forma rápida y eficiente.

2.2. Objetivos

El objetivo general de esta Tesis Doctoral es realizar aportaciones en metodologías basadas en la fotogrametría de bajo coste y rango cercano en escenarios agroforestales para aplicaciones específicas.

Para cumplir este objetivo general, se plantean diversos objetivos y sub-objetivos específicos:

1. Aplicación de la fotogrametría aérea multiespectral (visible y NIR) de bajo coste y rango cercano para análisis agronómicos:
 - adquisición de datos multiespectrales georreferenciados de alta resolución espacial y bajo coste sobre cultivos.
 - calibración vicaria de un sensor multiespectral de bajo coste desde paramotor mediante superficies económicas de control para su aplicación en cultivos.
2. Aplicación de la fotogrametría terrestre de bajo coste de rango cercano para estimar el rendimiento vitícola:
 - estimación de la producción vitícola en condiciones de campo mediante un método de bajo coste y no invasivo que sirva de herramienta de ayuda para el viticultor en la toma de decisiones con suficiente antelación.
 - modelado 3D de racimos a través de la hibridación de técnicas fotogramétricas y de visión computacional que garanticen semi-automatismo, flexibilidad y calidad, mediante una herramienta propia denominada PW (Photogrammetry Workbench).
 - desarrollo de diferentes técnicas de geometría computacional para conseguir la reconstrucción de la parte oculta del racimo mediante envolventes convexas.
 - desarrollo de algoritmos para la estimación de componentes de producción vitícolas.
3. Aplicación de la fotogrametría aérea de bajo coste y rango cercano para la gestión forestal:
 - desarrollo de una metodología de bajo coste, eficiente y precisa para la obtención de Modelos Digitales de Altura de Cubierta Vegetal en el área y momento de interés, destinados al inventario forestal.
 - integración de datos públicos correspondientes al terreno procedentes de sensores LiDAR en las nubes fotogramétricas forestales obtenidas con una plataforma de bajo coste de distinta resolución espacial y temporal.

- modelo de corrección entre ambas fuentes de datos que permitan minimizar los errores producidos por la georreferenciación.
- clasificación supervisada de la nube fotogramétrica de la vegetación basada en el color de las imágenes, aprovechando los valores radiométricos del espectro visible que poseen dichos puntos. El análisis se basa en los diferentes porcentajes entre los niveles digitales de dos pares de bandas (R-G y R-B) de acuerdo a un verde de referencia.

III. ARTÍCULOS CIENTÍFICOS

3. ARTÍCULOS CIENTÍFICOS

A continuación se muestran los tres artículos científicos publicados en revistas internacionales de impacto. Previo al artículo publicado, se introduce un breve resumen (en castellano) sobre el trabajo de investigación de cada uno de ellos.

3.1. Calibración radiométrica vicaria de un sensor multiespectral desde paramotor aplicado a la Agricultura de Precisión

El presente artículo propone la calibración vicaria como método de calibración radiométrico de un sensor multiespectral en un vuelo de alta resolución espacial mediante una plataforma tripulada aérea de bajo coste. El sistema propuesto consiste en un vuelo de tandem powered paraglider (TPPG) en el que se embarca la cámara multispectral en una plataforma autonivelada. La mayor ventaja que ofrece este tipo de plataformas tripuladas es su flexibilidad de vuelo, autonomía y capacidad de carga, permitiendo la integración de gran variedad de sensores con limitaciones poco significativas de peso y volumen.

Dicha calibración vicaria (Dianguirard and Slater, 1999) supone hacer una calibración radiométrica absoluta en condiciones de vuelo mediante campañas de medidas in situ. Dentro de esta modalidad se opta por el método absoluto basado en radiancias, ya que el nivel digital que define cada píxel tiene una relación directa con la radiancia detectada por el sensor (Hiscocks, 2011). Para realizar este ajuste radiométrico se eligen como superficies de control, superficies low-cost consideradas homogéneas y lambertianas (reflectividad pseudoconstante en todas las direcciones) bajo observaciones aéreas nadirales (Davranche et al., 2009). De las imágenes multiespectrales aéreas se extraen los niveles digitales de dichas superficies y con el espectroradiómetro desde tierra se obtiene su radiancia medida, estableciendo un modelo lineal para cada banda espectral del sensor. Las incógnitas se obtienen resolviendo el sistema sobredeterminado sin defecto de rango realizando una estimación robusta por medio del método Danés (Krarup, 1980), que rechaza las observaciones fuera de rango (errores groseros), dando una serie de pesos en

función de los residuos obtenidos en la iteración anterior. Para poder evaluar los efectos de la atmósfera en cuanto a la transferencia radiativa, se implementa el Modelo 6S (Vermote et al., 1997), que transforma la radiancia medida en el terreno a la obtenida a la altura del sensor. Finalmente, se validan los resultados mediante superficies de chequeo (naturales y artificiales), contrastando las radiancias derivadas del modelo con las directamente medidas. La zona de estudio se localiza en Albacete (Castilla La Mancha, España), en una finca situada a unos 21 km de la capital, propiedad del ITAP (Instituto Técnico Agronómico Provincial) en un viñedo de 5.4 ha. En la campaña radiométrica se caracterizaron las superficies de calibración usando el espectroradiómetro como detector del flujo radiante que proviene de dichas coberturas. Para evitar los efectos de la BDRF (Bidirectional Direction Reflectance Distribution), las superficies se caracterizaron en campo con número suficiente de muestras para poder rechazar anomalías en cuanto a la reflectancia espectral. Paralelamente, y para evitar variaciones atmosféricas significativas, se sobrevoló la zona de estudio en paramotor con una configuración de altura de vuelo y óptica en el sensor para un GSD de 0.08 m (a una altura de 145 m) y de 0.15 m (a una altura de 245 m), capturando imágenes multispectrales, escogiendo aquellas en las que aparecen el máximo número de superficies de control y chequeo. El nivel digital capturado por el sensor se corrigió en función del viñeteo y ruido de fondo sistemático de cada lente (Kelcey y Lucieer, 2012). Ya que son varias las imágenes que entran en el ajuste de la calibración, se ha tenido en cuenta un factor de homogeneización de luminancia entre fotos que permite neutralizar las diferencias de exposición. Además se incluye una incógnita común por imagen y constante por canal que absorbe posibles discrepancias existentes entre la atmósfera estándar y la real en cada imagen.

Al tratarse de radiometría aérea, y teniendo como objetivo la determinación de los parámetros superficiales, se debe aplicar un modelo atmosférico que parametrize la afección de la atmósfera en la propagación de la radiación teniendo en cuenta los procesos de dispersión y absorción (Hernández et al., 2011). El modelo aplicable en este caso de estudio ha sido el Modelo 6S para el vuelo más desfavorable (GSD de 0.15 m a la altura de 245 m). Según los datos obtenidos en la situación estudiada, esta influencia es mínima debido a que la columna atmosférica que la radiación atraviesa es muy pequeña desestimándose en los cálculos, demostrándose que la radiancia del sensor para una altura de 1 m de cada target por banda es idéntica a la radiancia considerando una altura

del sensor de 245 m calculada por el Modelo Bird 6S Reda, 2004, a partir de la radiancia medida con el espectroradiómetro.

Como resultado final de este estudio se muestran los parámetros de calibración de la cámara Mini-MCA, obtenidos para cada una de los seis canales. El error medio cuadrático (emc) de peso unidad a posteriori arroja un valor de 0.0043 y un coeficiente de determinación para el ajuste de 0.9940.

Con estos resultados se confirma la viabilidad de usar como alternativa low-cost al espectralón, lona de distintos colores para la calibración radiométrica vicaria así como la plataforma de vuelo utilizada sobre la que se embarca el sensor. Debido al bajo coste de las superficies de control, se obtiene gran cantidad de medidas al aumentar el número de tarjetas mejorando notablemente la calidad del ajuste. Con este estudio se pretende a su vez desarrollar una nueva metodología de teledetección que ayude en la toma de decisiones para la gestión sostenible de amplias extensiones de cultivos utilizando técnicas geomáticas de bajo coste. Por ello, como resultado del proceso de calibración radiométrica, se obtienen imágenes georreferenciadas aéreas de diferentes índices de vegetación multiespectrales sobre viñedos.

Palabras clave: *calibración radiométrica, índices de vegetación, agricultura de precisión, sensor multiespectral, calibración vicaria.*



Vicarious radiometric calibration of a multispectral sensor from an aerial trike applied to precision agriculture



Mónica Herrero-Huerta^a, David Hernández-López^b, Pablo Rodríguez-Gonzálvez^{a,*},
Diego González-Aguilera^a, José González-Piqueras^b

^a Department of Cartographic and Land Engineering, University of Salamanca, Higher Polytechnic School of Avila, Hornos Caleros 50, 05003 Avila, Spain

^b Institute for Regional Development (IDR), University of Castilla La Mancha, 02071 Albacete, Spain

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ABSTRACT

This article proposes a vicarious calibration as a radiometric calibration method using an onboard multispectral sensor and a low-cost manned aerial platform, PPG (powered paraglider) trike. The statistical analysis of the errors shows the precision reached with this methodology. The greatest advantage offered by this type of manned platforms is its flexibility of flight, autonomy and payload capacity, allowing multiple sensors to be integrated without constraints to weight and volume. The results were validated at two different heights in order to verify the solution obtained with the method, demonstrating the insignificance of relative atmospheric influence between the aerial platform and ground using this platform according to the radiative transfer model on a clear and sunny day. At the same time, the study aims to develop a new trend for remote sensing that will assist in decision making for the sustainable management of extensive crop areas using low-cost geomatic techniques. As a result of the radiometric calibration process, georeferenced images with different vegetation indices over vineyards are obtained.

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1. Introduction

The possibility of loading multispectral cameras on low-cost manned aerial platforms such as PPG trikes enables highly accurate radiometric studies to be performed. Therefore, it is desirable that the sensor should be subjected to a calibration in which the radiometric behavior of each pixel in the different regions of the spectrum is analyzed, using as “ground truth” the radiance obtained on different targets with the calibrated spectroradiometer (Honkavaara et al., 2009). The basis of this behavior lies in the fact that each body has a typical and different pattern of reflected/emitted energy when it is influenced by electromagnetic energy, which distinguishes it from other materials (Chuvieco and Huete, 2009) depending on atmospheric conditions and the sensor characteristics (Biggar et al., 2003).

The main limitation of PPG trikes to make use of methodologies based on quantitative remote sensing is the need to develop radiometric calibration methodologies to obtain validated radiance data. As advantages, PPG trikes are able to acquire higher spatial, spectral and mainly temporal resolution data with a lower associated cost (Hailey, 2005) and, also, the relative atmospheric corrections required for validating the radiance data are likely to

be insignificant on a clear and sunny day. The high spatial resolution data available from conventional platforms, such as satellites and manned aircrafts, is usually limited to a Ground-Sample Distance (GSD) of 50 cm/pixel. Instead, PPG trikes are capable of flying lower than a conventional manned aircraft and therefore acquire images of higher resolution, reaching up to 5–10 cm/pixel. In addition, the ease of flight planning permits better temporal resolution than classic photogrammetric flight planning (Hernandez-Lopez et al., 2013). In satellite systems, temporal resolution is limited by the coverage patterns of the satellite's orbit, involving lengthy periods in the delivery of the results (unfavorable temporal resolution) (Berni et al., 2009). Regarding unmanned aerial systems (UAS), the payload capacity and volume of onboard sensors as well as the limited flight autonomy means that the mapping and monitoring of large surfaces and ground covers are unviable. Last but not least, the progress of microelectronics in the field of navigation equipment (GNSS/IMU-Global Navigation Satellite System/Inertial Measurement Unit) has made it possible to provide these low-cost manned platforms with a quality solution to determine the spatial and angular position of the sensors and consequently their trajectory.

A key factor in the suitability of close-range remote sensing for vegetation analysis (i.e. precision agriculture) is based on the fact that such sensing procedures are non-destructive and non-invasive, providing similar accuracy to destructive field methods (Zhang and Kovacs, 2012). More specifically, the spectral signature

* Corresponding author.

E-mail address: pablorgsf@usal.es (P. Rodríguez-Gonzálvez).

of a given crop is directly related to its phenological, physiological and morphological characteristics, such that any change in the plant will also disturb its reflectance (Lass and Callihan, 1997; Schmidt and Skidmore, 2003). These differences in the intrinsic spectral behavior of each species allow their discrimination and mapping by analysis techniques and digital classification. This is why the spectral signatures of different types of vegetation can be assessed, supported by vegetation indices and the subsequent biophysical magnitudes used in agricultural applications.

The most widely used and most familiar vegetation index is the Normalized Difference Vegetation Index (NDVI) developed by Rouse et al. (1974), which is based on contrasts between maximum absorption in the red spectral region, because of chlorophyll pigments, and maximum reflection in the infrared region, caused by the cell structure of leaves and reflection of the cover due to its structure. Despite its intensive application, in cases of dense covers or those consisting of several layers the NDVI becomes saturated, such that a non-linear relationship with biophysical parameters such as the Leaf Area Index (LAI) (Baret and Guyot, 1991) is seen. The next generation of vegetation indices were developed taking into account the linearity of the cover fraction and the leaf area index, but normalizing soil brightness and color (Gilbert et al., 2011). As implied by their name, these indices refer to the soil and include the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) and the Modified Soil Adjusted Vegetation Index (MSAVI) (Qi et al., 1994).

Other indices have been designed taking into account the spectral behavior of the soil in study areas, maintaining the sensitivity to biophysical magnitudes such as the Generalized Soil Adjusted Vegetation Index (GESAVI) (Gilbert et al., 2002). GESAVI showed good results for its linearity with LAI and soil noise reduction, simulating reflectances with radiative transfer models and with experimental data. A study by Broge and Leblanc (2001) addressing radiative transfer models has shown that the MSAVI is the best LAI estimator in terms of sensitivity-to-cover effects, variations in the cover parameters and the spectral properties of the soil. In the present work, the above vegetation indices were calculated in order to show the potential of multispectral calibrated images in agronomy.

Many studies have been carried out using multispectral and hyperspectral aerial and satellite images in the evaluation of crops (Herwitz et al., 2004; Chen et al., 2006; Zarco-Tejada et al., 2004). In fact, some authors have published works that, using multispectral, thermal or other conventional cameras on board small aircraft or unmanned helicopters, demonstrate the viability of these as platforms for image acquisition for plant studies (Esposito et al., 2007; Xiang and Tian, 2007; Turner et al., 2011; Zhao and Peng, 2006). However, to date there are no studies in which low-cost manned platforms such as PPG trikes have been used for crop monitoring. These offer an ideal platform for the study of large extensions of crops due to the above requirements.

The purpose of this article is to evaluate a new methodology aimed at acquiring georeferenced multispectral data of high spatial resolution after a radiometric calibration of the multispectral sensor for the monitoring of crops and the detection of areas with pathologies or hydric and nutritional deficiencies. To validate the methodology, a cultivated area of 5.4 ha was studied via aerial-trike overflights at different heights, using open-source software and tools. Thus, for vicarious calibration a GNU Octave (GNU, 2013) code was implemented.

The article is structured as follows: after the Introduction, Section 2 defines the method of vicarious radiometric calibration. In Section 3, the instruments used and the method developed are described. The experimental results and their discussion are given in Section 4, and the most significant conclusions are outlined in Section 5.

2. Vicarious radiometric calibration

The analysis of data captured by multispectral cameras requires prior knowledge of the radiometric calibration parameters of each channel to obtain correct interpretations. The calibration method chosen here was vicarious calibration (Dinguirard and Slater, 1999; Hernández-López et al., 2012), which involves performing an absolute radiometric calibration under flight conditions in an *in situ* radiometric measurement campaign. In this mode, the absolute method based on radiances was chosen because the digital level (DN) that defines each pixel is directly related to the radiance detected by the sensor (Hiscocks, 2011). The method based on radiances is theoretically more accurate than those based on reflectance, because it has an uncertainty of approximately only 2.8% as compared with 4.9% for the latter case (Biggar et al., 1994). This lower value is derived from the calibration and stability of the spectroradiometer required for calibration.

To carry out the radiometric adjustment, low-cost surfaces compared to other more expensive lambertian ones, have been selected as the ground control targets (invariant targets) to approximate comparable and homogenous spectral behavior under nadir observation angles to flight measurements (Davranche et al., 2009). In addition, via various laboratory tests and field studies the invariant reflective capacity for a period of time in which these surfaces were not damaged was confirmed. From the multispectral aerial images, the digital levels of these targets can be extracted and the radiance measured is obtained with the spectroradiometer on the ground, establishing a linear model for each spectral band of the sensor. To assess the effects of the atmosphere in terms of radiative transfer, the 6S Model (Vermote et al., 1997) was implemented, which transforms the radiance measured at the ground into that obtained at the height of the sensor. Finally, the results were validated with natural and artificial check targets (pseudo-invariant targets), contrasting the radiances calculated by the calibration parameters with those measured directly in the field.

Fig. 1 shows the workflow followed in the radiometric calibration process.

3. Materials and methods

3.1. Materials

The following equipment was employed for data acquisition:

- A GNSS device, Leica 1200. This consists of a RTK dual frequency receiver and geodetic GPS L2C and double dual-frequency antenna with L2C and serves to georeference control and check targets.
- A six-channel multispectral camera: Tetracam Mini-MCA. Each of the six channels of the camera is constituted by a CMOS (Complementary Metal–Oxide–Semiconductor) sensor and a filter with a preset performance against the spectral range. The spectral response of CMOS sensors is not uniform due to quantum efficiency and sensitivity. Neither do filters exhibit homogeneous transmission between each other. The effect of the combination of CMOS and the six filters results in a reduction in camera radiance, different per each wavelength. The camera specifications are defined in Table 1. The choice of the filter wavelengths (detailed in Table 2) was optimized for the evaluation of the particular behavior of the vegetation, avoiding areas of atmospheric absorption.
- A manned aerial platform supported by a powered paraglider (PPG) trike built by Airges. Its technical specifications are shown in Table 3. The Mini-MCA camera was loaded onto the PPG trike using an auto-stabilized mounting platform.

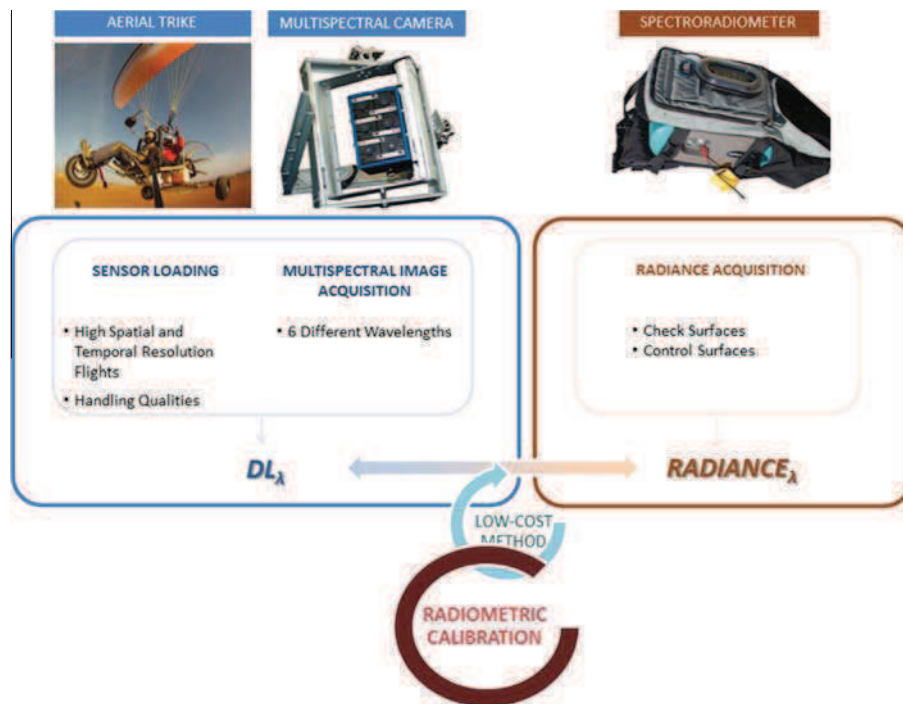


Fig. 1. Workflow of the vicarious radiometric calibration process.

Table 1
Technical specifications of the Mini-MCA multispectral camera.

Parameter	Value
Number of channels	6
Weight	700 g
Resolution	1.3 Mp per Channel
Image size	1280 × 1024 pixels
Radiometric resolution	8 bits
Capture speed	1.3 frames/s
Pixel size	5.2 μm
Focal length	9.6 mm

Table 2
Channel specifications of the Mini-MCA camera.

Channel	λ_{min} (nm)	λ_{max} (nm)	Exposure time (%)
0	740	820	100
1	510	550	130
2	650	690	125
3	660	740	100
4	720	760	100
5	760	840	100

Table 3
Technical specifications of the manned aerial platform, PPG trike.

Parameter	Value
Empty weight	110 kg
Maximum load	220 kg
Autonomy	3.5 h
Maximum speed	60 km/h
Motor	Rotax 503
Tandem paraglide	MACPARA Pasha 4
Emergency system	Ballistic parachutes GRS 350
Gimbal	Stabilized with 2 degrees of freedom
Minimum sink rate	1.1
Maximum glide	8.6
Plant surface	42.23 m ²
Projected area	37.8 m ²
Wingspan	15.03 m
Plant elongation	5.35
Central string	3.51 m
Boxes	54
Zoom factor	100%

- An aluminum multi-sensor gimbal (stabilized platform) where the multispectral camera is affixed. In particular, the gimbal includes two servomotors arranged on the x and y axes to maintain the vertical position of the camera along the flight path with precision. The servomotors are controlled by an Arduino board, which incorporates an IMU with 6 degrees of freedom: 3 accelerometers with a range of $\pm 3.6 \text{ G m s}^{-2}$, a double-shaft gyroscope (for pitch and roll) and an additional gyroscope for yaw (both gyroscopes have a measurement range of $\pm 300^\circ/\text{s}$). The software developed for the control of the device was based on Quadl_mini V 20 software, with DCM (Direction Cosine Matrix) as the management algorithm of the IMU (Premierlani and Bizard, 2013).
- A low-cost GNSS system based on a single-frequency receptor, with a signal reception of GPS constellation and SBAS (Satellite Based Augmentation System) (NavCen, 2008). The GNSS

antenna is installed on the camera platform close to the optical center of the camera to minimize the baseline. In order to contrast the GNSS altitudinal accuracy that affects the final GSD, a DigiFly VL100 barometer was installed. Thus, horizontal positioning during flight was performed by the NMEA (National Marine Electronics Association) protocol of the GNSS system using RTKNAVI software (Takasu, 2009), with corrections from the ground from another similar board equipment, allowing DGPS accuracies better than 1.5 m in planimetry and 2 m in altimetry to be achieved in real time, and better than 0.5 m in 3 dimensions in postprocessing.

- A general purpose FieldSpec 3 ASD (Analytical Spectral Devices) spectroradiometer, used for the different targets (control and check) and specifically designed to acquire spectral measurements (radiance and irradiance) in the visible and near infrared ranges. The main technical specifications of the spectroradiometer are shown in Table 4.

Table 4

Technical specifications of the FieldSpec 3 ADS Spectroradiometer.

Parameter	Value
Spectral range	350–2500 nm
Shooting time	0.1 s
Spectral resolution	1 nm
Field of view	25°

3.2. Methods

3.2.1. Flight planning and execution

The study area was located in an experimental field of the ITAP (Provincial Agricultural Technical Institute) near Albacete (Castilla La Mancha, Spain), about 21 km from the capital. Data collection was performed on the 20th of June 2013 around a vineyard, grass and a *Papaver somniferum* crop of 5.4 ha.

Proper flight planning is important to ensure that the data captured will fit the theoretical parameters pursued; it also optimizes available resources and ensures a higher quality image, minimizing capture time.

First, the study area and subsequently the plot flight paths were defined. Then, the flight planning process defined the position and orientation of the camera, the design of different blocks of images, determination of the overlaps between different images, the necessary shot angles and guarantee of the scale through choice of the pixel size on the ground (GSD). A GSD of 0.08 m and 0.15 m was selected in this study.

The geomatic information required for the flight planning process can be obtained freely from the National Center of Geographic Information in Spain (CNIG), from its National Aerial Orthoimage Plan (PNOA, 2009) with a GSD of 0.25 m and a Digital Terrain Model (DTM) with a 5-m grid resolution.

Flight planning was performed by considering the relationship between flight altitude over the ground (H), the GSD, the focal length of the sensor (f) and pixel size, as described in Eq. (1).

$$\frac{f}{H} = \frac{\text{pixel size}}{\text{GSD}} \quad (1)$$

Considering Eq. (1), the characteristics of the camera (Table 1) and the required GSD of 0.08 m and 0.15 m, flight altitudes over the ground of 145 m and 245 m are obtained respectively. Also, additional restrictions, such as a minimum forward overlap of 60% and a minimum side overlap of 20% were established. The flight planning obtained is outlined in Fig. 2, where rectangles are the areas capture by each image shot in the point position.

3.2.2. Field data acquisition

In the study area, control and check targets were selected and positioned (Fig. 3) taking the GSD dimension into account.

The control and check targets used in the data collection are specified for both flights in Table 5.

In the radiometric campaign, calibration targets were characterized by the spectroradiometer as radiant flux detector. During data acquisition, the angle between the gun of the spectroradiometer and the targets measured was kept as orthogonal as possible, taking two measurements with an average of 30 spectral measurements per cover. In order to avoid the BRDF effects, the tarps have been characterized at field with enough number of samples to reject spectral reflectance anomalies.

Figs. 4 and 5 show the spectral signatures of the colored and grayscale tarps acquired in the radiometric campaign. The reflectance of these targets was obtained as the ratio of the reflected radiance of each cover and the irradiance provided by a reference target (Spectralon® 99%), both measured with the spectroradiometer.

At the same time, and in order to avoid significant atmospheric variations, a planned PPG trike flight was conducted over the study area with a 0.08 m GSD (at 145 m height) and 0.15 m GSD (at 245 m height), capturing multispectral images (Fig. 6) and finally choosing those in which the maximum number of control and check targets appeared.

3.3. Calibration methodology and fitting model

Measured radiance serves as ground truth, establishing a connection with the digital level of the corresponding wavelength. On one hand, radiance was measured in a spectral range of 350–2500 nm with a nanometer resolution. On the other, the Mini-MCA recorded digital levels in its 6 channels, characterized by the response of the filters and CMOS per wavelength. Thus, the radiometric measurements were resampled and standardized for the spectral resolution of the camera.

In addition, digital levels were corrected for vignetting and the systematic background noise produced by each lens (Kelcey and Lucieer, 2012). The vignetting study was performed at the laboratory with uniform lighting, capturing images of a white pattern with low specular reflection (Zheng et al., 2009). The systematic background noise was evaluated at the laboratory under the absence of lighting conditions and analyzing the average response of the camera per channel for its different exposure times.

Because there are several images involved in calibration adjustment, a homogenization factor of luminance between images was taken into account to neutralize the exposure differences. These differences are caused by changes in lighting between different image captures and the exposure time of each channel, according



Fig. 2. Flight planning of 0.15 m GSD (at 245 m height) (a) and 0.08 m GSD (at 145 m height) (b).

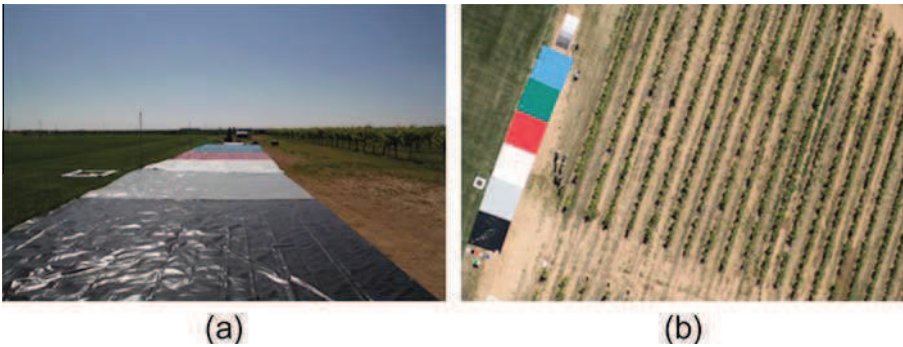


Fig. 3. Terrestrial image of the control targets for the radiometric calibration (a) aerial image of the calibration targets and study area (b).

Table 5
Description of the control and check PCV targets.

Control	Type	Material	Size	Color
Control targets	Artificial	PVC tarp	5 m × 1 m	Grayscale (5 steps)
		PVC tarp	5 m × 1 m	Black Gray White Red Green Blue
Check targets	Artificial	PVC surface	0.55 m × 0.35 m	Black Gray White Red Green Blue
		Brown wrapping paper Cork Cardboard Grass Ground		
	Natural	Grapevine Papaver somniferum		

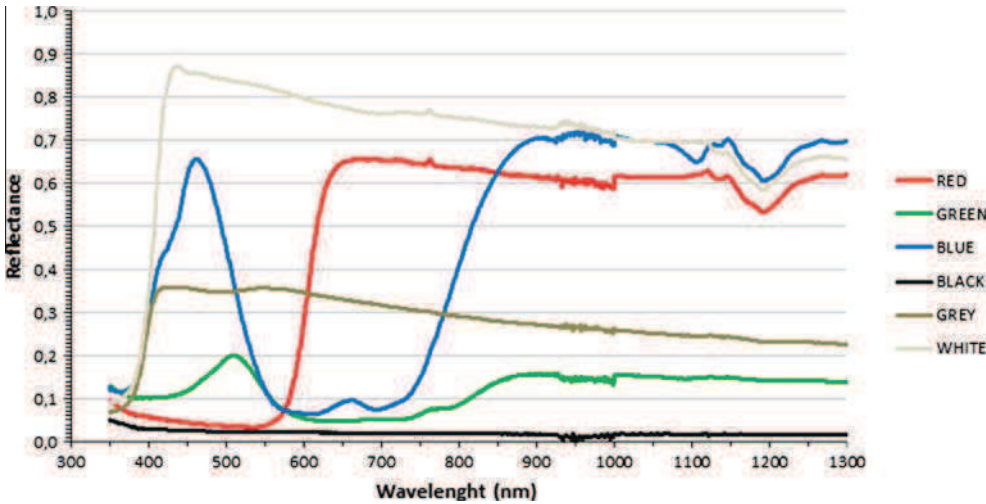


Fig. 4. Spectral signature from 350 nm to 1300 nm of the control targets (PVC tarps) obtained in the field with the spectroradiometer.

to the manufacturer. This factor corrects digital levels and depends on the channel and the image. Also, a common unknown per image and invariant for each channel was included in order to absorb possible discrepancies between the standard and real atmosphere for each image.

The mathematical model used is shown in the following figure (Fig. 7), where \mathbf{X} is the vector of calibration coefficients

(unknowns); \mathbf{A} is the design matrix (corrected digital levels of control targets in the images) and \mathbf{L} is the vector of independent terms (radiance measures of control targets).

Eq. (2) summarizes this model:

$$\mathbf{L} = \mathbf{F}_0 + \mathbf{F}_1 \cdot \mathbf{DN}_c, \tag{2}$$

where

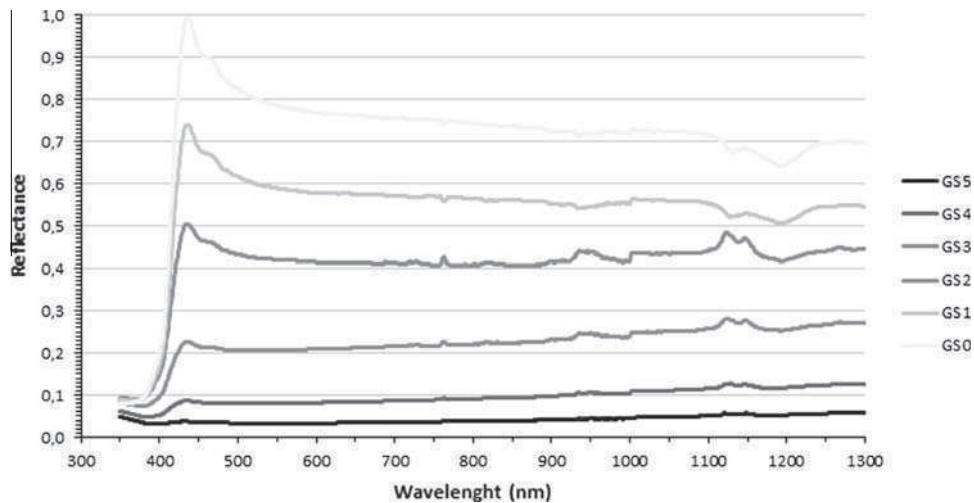


Fig. 5. Spectral signature from 350 nm to 1300 nm of the control targets (Grayscale tarp) obtained in the field with the spectroradiometer.

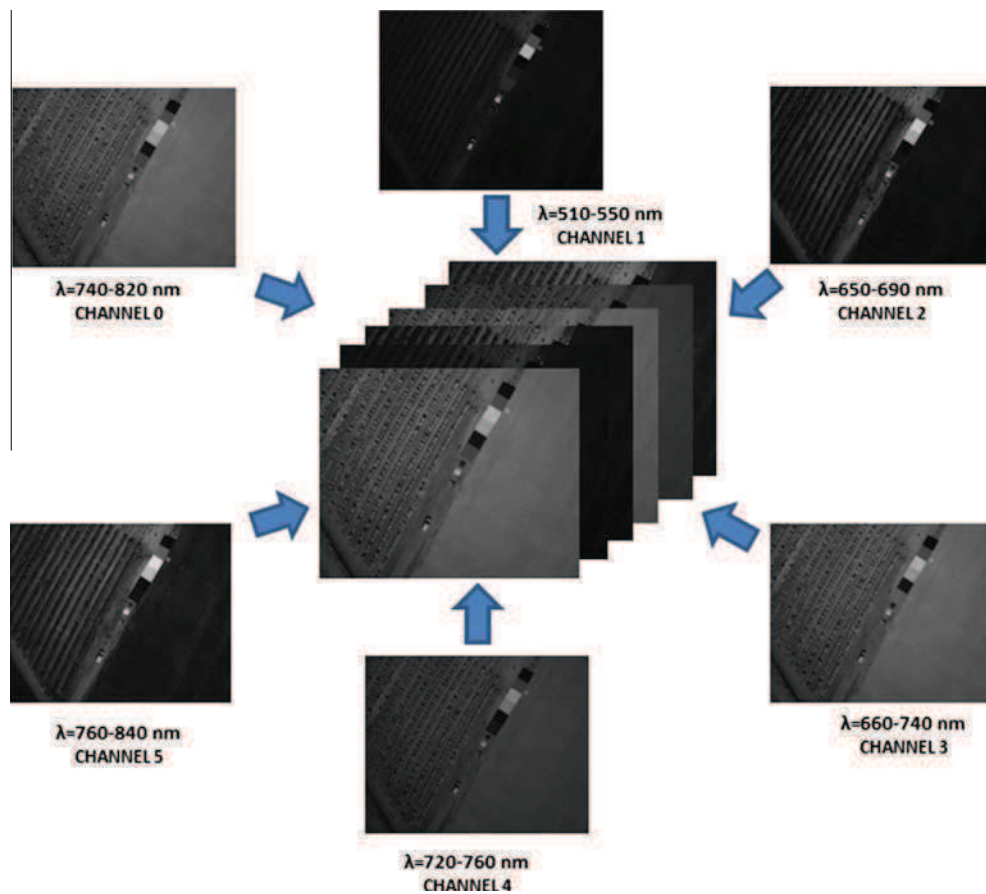


Fig. 6. Multispectral images used in the radiometric calibration process.

L is the measured radiance of each control target,
 DN_c is the digital level of control targets corrected by luminance, vignetting and the systematic background noise,
 F_0 is the offset calibration coefficient of each channel,
 F_1 is the gain calibration coefficient of each channel.

The unknowns are obtained by solving the over-determined system without rank default, performing a robust estimation with the Danish Method (Krarup et al., 1980), which rejects the out-of-range observations (outliers), giving a series of weights based on the residual values obtained in the previous iteration.

3.4. Atmospheric correction

In aerial radiometry, the aim is to determine physical values at ground level. In this way, an atmospheric model must be applied to study the behavior of radiance propagation because of scattering and absorption processes (Hernández-López et al., 2011). In this study case, the 6S radiative transfer model (Vermote et al., 1997) was applied for the less favorable flight (0.15 m GSD flight at 245 m height).

With regard to atmospheric parameters, the values of aerosol optical depth (AOD) were taken from AERONET (aerosol robotic

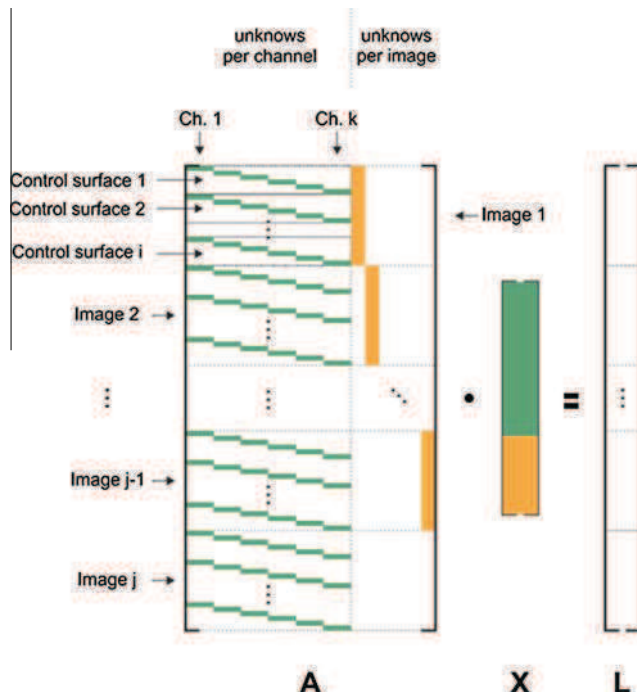


Fig. 7. Mathematical model of the radiometric calibration process.

network). Owing to the absence of closer stations, the AOD value was extracted as the average of the values of two closest stations, approximately 200 km from Albacete in the North-West and South-East directions (Madrid and Burjassot, respectively).

For each control target, sun direction was obtained at the moment of image acquisition, expressed by the geodetic azimuth and the zenith angle from the vertical. For this calculation, the Solar Position Algorithm (SPA) library (Reda and Andreas, 2004) was used. The input parameters were obtained from known flight data and GNSS measurements. Once solar direction had been calculated, the atmospheric parameters were obtained from the 6S Model, which creates an atmospheric profile on the control targets involved in the calibration process for each of the channels. Among the atmospheric parameters calculated, irradiance per image and channel and radiance and reflectance at ground and sensor per target and channel were included.

According to the data obtained, the relative influence of the atmosphere is minimal because the atmospheric column spanned by the radiation is unimportant and can be neglected in the calculations, demonstrating that sensor radiances at 1 m or 245 m height (using 6S model (Vermeote et al., 1997)) were fairly similar to those measured at ground level with the spectroradiometer.

3.5. Derived geomatic products

Geomatic products are characterized by their spatial, spectral, radiometric and temporal resolution (Aber et al., 2010). In the present case, spatial resolution was limited by a GSD of 0.15 m, considered sufficient for this type of agricultural study. Temporal resolution was established considering the phenological aspects of the crop and environmental aspects. Regarding spectral resolution, this is limited to the band width of the six filters chosen to detect certain types of plant behavior in the most appropriate spectrum, avoiding areas of atmospheric absorption.

Advances in computer vision, photogrammetry and new low-cost GNSS and IMU systems make it possible to obtain orthoimages generated from images captured with a non-metric digital camera aboard a low-cost aerial platform (Aber et al., 2010).

Finally, images were georeferenced considering Coordinate Reference System (CRS) ETRS89 UTM 30 (EPSG code 25830), which is required by Spanish legislation in all geomatic products. In the navigation phase, which uses a GNSS, WGS84 CRS was employed (EPSG code 4326).

4. Experimental results and discussion

Below, the calibration parameters of the Mini-MCA camera are reported. F_0 is the offset coefficient and F_1 is the gain coefficient (Tables 6 and 7) obtained for each of the six channels achieved in the mathematical fitting of the two flights with different GSD. The *a posteriori* variance in unit weight shows a value of $0.0043 \text{ W m}^{-2} \text{ sr}^{-1}$ and a correlation coefficient of adjustment, R^2 , of 0.9940.

In both flights, the detection of outliers was studied in order to avoid outliers. Standardized errors were calculated with the Pope Statistical Test (Pope, 1976), the maximum standardized residual of 2.800 remaining under the threshold of 3.916 established at the 95% of confidence level with a Tau distribution.

Together with the detection of outliers, internal fiability was tested by means of redundancy number analysis. As a result, all the equations contribute to approximately the same extent, without there being an increased presence of certain observations, due to the internal design of the proposed system, confirming the absence of outliers in the observations. The redundancy numbers of the adjustment entail a range between 0.9306 and 0.9995 for both flights.

A statistical analysis of the resulting coefficients for both flights was performed in order to assess their differences. The statistical parameter was defined as:

$$Z = \frac{\mu_1 - \mu_2}{\sqrt{\sigma_{\mu_1}^2 + \sigma_{\mu_2}^2}} \quad (3)$$

where σ_{μ_1} is the standard error of the mean value calculated as:

$$\sigma_{\mu_1} = \frac{\sigma}{\sqrt{n}} \quad (4)$$

The critical value for a two-tailed test at 5% of significance is ± 1.96 using a normal distribution. According to the results shown in Table 8, the resulting coefficients of both flights show no significant differences, so the null hypothesis of both samples belonging to the same distribution can be accepted.

Table 6

Radiometric calibration coefficients of the multispectral camera for 0.08 m GSD flight (at 145 m height) in radiance units ($\text{W m}^{-2} \text{ sr}^{-1}$).

Channel	F_0 value	F_1 value
0	−60.5584	2627.3057
1	19.2122	4002.9353
2	2.7057	3108.6876
3	−13.0825	2590.2099
4	−84.4579	4349.9835
5	−60.9567	2660.1684

Table 7

Radiometric calibration coefficients of the multispectral camera for 0.15 m GSD flight (at 245 m height) in radiance units ($\text{W m}^{-2} \text{ sr}^{-1}$).

Channel	F_0 value	F_1 value
0	−77.1444	2548.2911
1	15.6807	3798.3712
2	−16.4305	2930.0517
3	−20.3672	2428.5566
4	−89.7453	4250.6229
5	−67.3736	2947.6022

Table 8

Statistical comparison of the radiometric calibration coefficients of both flights.

Channel	F_0		F_1	
	Z score	P value	Z score	P value
0	0.0143	0.9886	0.0399	0.9682
1	0.0033	0.9974	0.0979	0.9220
2	0.0167	0.9866	0.0922	0.9265
3	0.0066	0.9948	0.0886	0.9294
4	0.0046	0.9963	0.0406	0.9676
5	0.0055	0.9956	−0.1341	0.8933

To address statistical significance, two complementary hypotheses were established. In this case, H_0 establishes that residual values are distributed according to a normal distribution with mean zero, whereas H_a considers that the distribution mean is a nonzero value. The F_0 and F_1 parameters were studied in both flights, obtaining p -values greater than 0.279 and less than 0.001 respectively. Working with a 95% confidence interval, the F_0 coefficient may be negligible but not the F_1 coefficient. This is in agreement with the specifications of the manufacturer in that the offset parameter is negligible. To validate the results, the mean of the absolute values of the residuals per channel of the targets (control and check targets) between the measured and calculated radiance was used. This parameter was always below $0.01 \text{ W m}^{-2} \text{ sr}^{-1}$ (Table 9).

Because the residuals in the 0.08 m GSD flight were lower than in the 0.15 m GSD flight, the parameters at 0.08 m GSD flight were analyzed in order to be used in future studies. Fig. 8 shows a

Table 9Mean of the absolute values of the residuals per channel in $\text{W cm}^{-2} \text{ sr}^{-1}$.

Flight GSD(m)/height(m)	Ch. 0	Ch. 1	Ch. 2	Ch. 3	Ch. 4	Ch. 5
0.08/145	36.22	43.71	42.77	35.82	37.32	31.46
0.15/245	45.32	66.29	53.46	52.07	47.41	54.88

representation of the mean radiance errors of the different control targets per channel used in the calibration process.

A statistical study was conducted to check the calibration process Table 10 shows the statistical parameters of errors (Eq. (5)) calculated as differences between ground radiance measurement with the spectroradiometer on check targets and radiance calculated by digital levels and the parameters resulting from the calibration process (Eq. (6)).

$$v = L_{\text{measured}} - L_{\text{calculated}} \quad (5)$$

$$L_{\text{calculated}} = F_0 + F_1 \cdot DN_c \quad (6)$$

where

v : check target error,

L_{measured} : check target measured radiance,

$L_{\text{calculated}}$: check target calculated radiance,

DN_c : digital level corrected by variations in exposure time between channels, vignetting and systematic background noise,

F_0 : offset calibration coefficient from each camera channel,

F_1 : gain calibration coefficient from each camera channel.

The standard deviation (σ) (Eq. (7)), root mean square error ($rmse$) (Eq. (8)) and average error $|\bar{v}|$ in absolute values (Eq. (9)) are shown in Table 10, and are defined as follow:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (v_i - \bar{v})^2} \quad (7)$$

$$rmse = \sqrt{\frac{1}{n} \sum_{i=1}^n (v_i)^2} \quad (8)$$

$$|\bar{v}| = \frac{\sum_{i=1}^n |v_i|}{n} \quad (9)$$

This shows that most of the check targets, assumed to be pseudo-invariant targets, are suitable for the validation of radiometric calibration. In general, artificially colored uniform surfaces, such as PVC targets, provided the best precision in the six channels

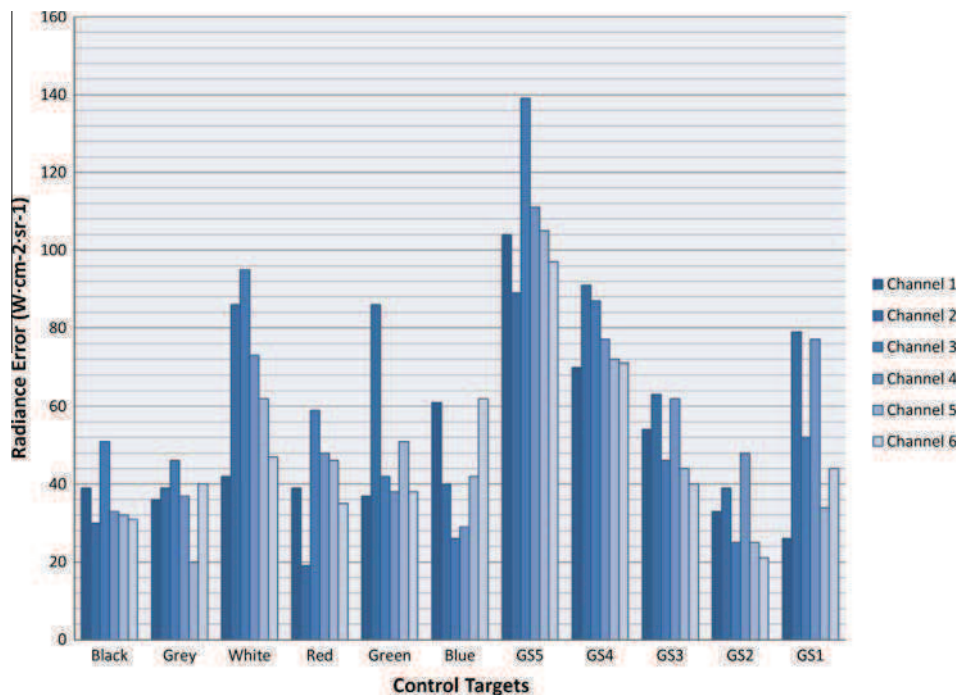
**Fig. 8.** Mean of the radiance errors of the different control targets ($\text{W m}^{-2} \text{ sr}^{-1}$) per channel.

Table 10

Statistical values of errors in the vicarious calibration performed on different check targets expressed in radiances ($\text{W m}^{-2} \text{sr}^{-1}$), where σ is the standard deviation, $rmse$ is the root mean square error, and $|\bar{v}|$ is the average absolute error value.

Target	Statistical parameter	Channel 0	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5
Blue PVC	σ	61.33	54.88	17.00	33.03	44.62	63.75
	$rmse$	68.49	47.77	86.02	140.20	74.55	55.22
	$ \bar{v} $	43.25	43.25	84.75	137.25	63.75	45.00
Gray PVC	σ	181.10	80.38	87.59	68.52	93.27	42.43
	$rmse$	158.47	417.84	272.76	140.18	104.63	37.41
	$ \bar{v} $	124.25	412.00	262.00	127.00	103.00	33.00
Green PVC	σ	49.11	59.61	80.64	46.12	68.77	43.07
	$rmse$	151.11	189.90	137.55	140.78	151.22	177.71
	$ \bar{v} $	145.00	182.75	118.50	135.00	139.00	173.75
Red PVC	σ	146.71	20.94	144.03	112.53	198.00	111.80
	$rmse$	270.67	42.56	588.37	352.01	350.12	225.13
	$ \bar{v} $	239.00	38.50	575.00	338.25	305.25	203.25
Black PVC	σ	15.41	37.10	18.63	41.84	38.20	28.52
	$rmse$	167.51	222.40	211.18	186.09	180.31	157.67
	$ \bar{v} $	167.50	222.38	211.18	186.05	180.28	157.65
White PVC	σ	214.36	133.39	195.42	209.22	230.73	167.65
	$rmse$	560.86	1492.48	1063.80	666.12	590.34	491.68
	$ \bar{v} $	529.25	1488.00	1050.25	641.00	555.50	469.75
Ground	σ	9.90	11.31	7.07	24.75	28.99	12.02
	$rmse$	99.25	149.21	287.04	95.12	113.37	42.36
	$ \bar{v} $	99.00	149.00	287.00	93.50	111.50	41.50
Brown Wrapping Paper	σ	58.94	84.68	81.93	103.23	111.70	101.10
	$rmse$	51.27	73.98	153.66	94.62	96.43	89.79
	$ \bar{v} $	47.67	63.00	138.33	80.33	87.33	86.67
Cardboard	σ	57.14	52.00	73.60	138.30	88.06	93.22
	$rmse$	436.17	591.19	731.14	466.21	421.84	351.67
	$ \bar{v} $	−433.67	−589.67	−728.67	−452.33	−415.67	−343.33
Grass	σ	141.20	69.85	48.06	54.24	100.34	112.49
	$rmse$	129.85	102.45	58.18	63.52	90.71	112.71
	$ \bar{v} $	127.40	81.20	42.40	44.20	75.60	106.80
Grapevine	σ	–	–	–	–	–	–
	$rmse$	169.00	59.00	42.00	22.00	294.00	128.00
	$ \bar{v} $	169.00	59.00	42.00	22.00	294.00	128.00
Cork	σ	14.14	26.16	72.12	65.05	91.22	29.70
	$rmse$	417.12	330.02	629.07	473.24	416.52	384.57
	$ \bar{v} $	417.00	329.50	627.00	471.00	411.50	384.00
<i>P. somniferum</i> .	σ	–	–	–	–	–	–
	$rmse$	469.00	185.00	355.00	225.00	334.00	345.00
	$ \bar{v} $	469.00	185.00	355.00	225.00	334.00	345.00

of the spectrum, while more heterogeneous surfaces such as the ground or vegetation afforded poorer results. These are anisotropic and less homogeneous surfaces than PVC, with higher variations in the radiance leaving the target and its reflectance. This produces a slight increase in its $rmse$ and σ .

All these results confirm the feasibility of using tarps of different colors as a low-cost alternative to spectralon with certain limitations for vicarious radiometric calibration. As a result, several measurements can be obtained by increasing the number of targets and hence improving the quality of the mathematical fitting.

Although not aiming to investigate the performance of the different vegetation indices, an example of the product generated using the georeferenced multispectral reflectance images is provided in this work in order to highlight its potential in agricultural studies. Four multispectral vegetation indices were selected taking into account that they are widely applied in agronomy owing to their sensitivity to vegetation and their normalization of soil background brightness and color: NDVI, SAVI, MSAVI and GESAVI. The latter was parameterized for the soil characteristics in the study area.

These images were processed with algorithms defined in the 2nd and 5th channel of the multispectral sensor (670 and

800 nm) (Fig. 8) through an implemented code in GNU Octave software.

The reflectance of each pixel was obtained from the calculated radiance and irradiance per channel acquired previously with a calibrated PVC target that appeared on the image, according to Eq. (10) for each sensor channel [24], under the assumption of a Lambertian surface.

$$\rho = \frac{L_{\text{calculated}} \cdot \pi}{E} \quad (10)$$

where $L_{\text{calculated}}$ is the radiance calculated from each target and E is the irradiance per channel.

Although the indices addressed here do not have the same range of variation, all of them identify the plant trellis in the scene, as can be seen in Fig. 9. They enhance the photosynthetic activity in the scene, showing not only the presence of the vineyard plants but also other small plants between the rows. The darkest areas correspond to non-vegetated areas. These images can also be compared quantitatively to other flight dates allowing the vineyard to be monitored for the managing of nutrients, diseases or water supply within the plot.

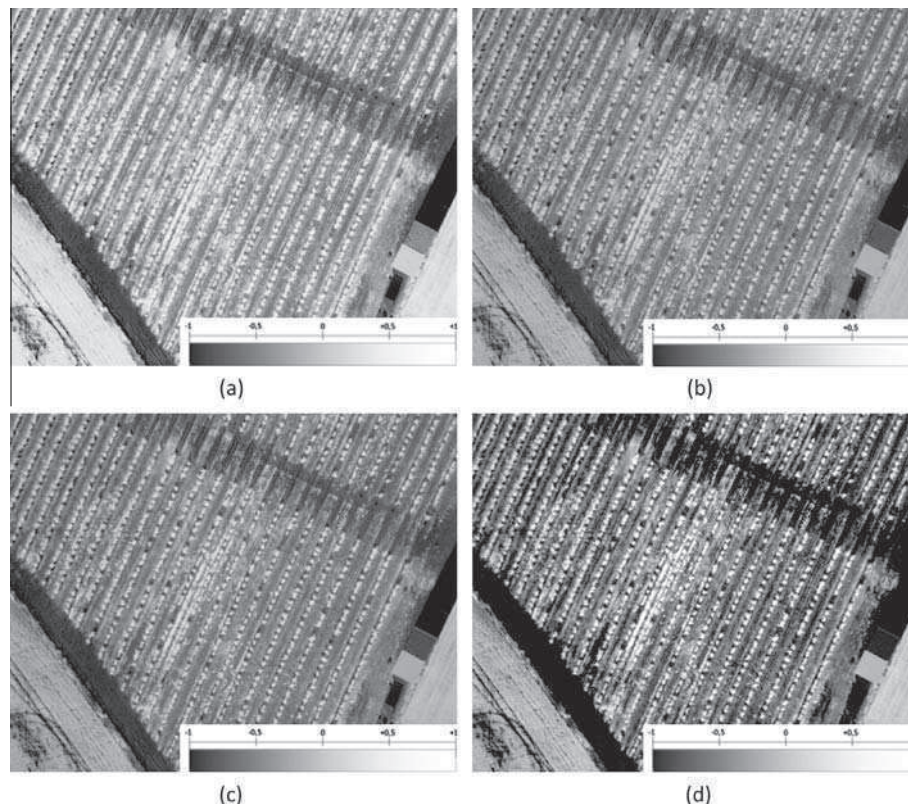


Fig. 9. Different plant indices in the vineyard area derived from the radiometric calibration: (a) NDVI Image, (b) SAVI Image, (c) MSAVI Image and (d) GESAVI Image.

5. Conclusions

This paper describes a successful methodology for radiometric calibration using the vicarious method of a multispectral Mini-MCA camera aboard a low-cost manned aerial platform and using low-cost targets of invariant reflectivity material. The static analysis of the errors confirms the validity of the method. For this purpose, a flight at two different heights was carried out to test adjustment stability, the calibration coefficients being statistically consistent in both cases, demonstrating insignificant relative atmospheric effects occurring in flights below 300 m on a clear and sunny day. In fact, this is the maximum height at which these platforms are permitted to fly according to Spanish legal constraints. The results confirm a new trend for low-cost remote sensing, together with the use of the latest computer vision techniques and open-source geomatic tools. In this study case, the calibrated geomatic products can be used to successfully evaluate and classify large areas of different crops, allowing decisions to be made about irrigation, nutritional support and crop development through accurate georeferenced and calibrated multispectral images. Compared to classic aerial photogrammetric platforms (aircraft), the proposed methodology cuts costs. Regarding satellite systems, their temporal and spatial resolution generates a major limitation in applications to crops. The potential of this PPG trike system is evident, with the possibility of being able to load it with a large number of sensors that extend multispectral studies, affording the advantage of a flying height that minimizes the need for atmospheric corrections. Here, the potential of deriving quantitative magnitudes such as vegetation indices is also shown. Future works will address the assimilation of the calibrated images into agronomic models to evaluate their consistency with advanced biophysical variables.

References

- Aber, J.S., Marzoff, L., Ries, J., 2010. *Small-Format Aerial Photography: Principles, Techniques and Geoscience Applications*. Elsevier Science, The Netherlands.
- Baret, F., Guyot, G., 1991. Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sens. Environ.* 35, 161–173.
- Berni, J., Zarco-Tejada, P.J., Suarez, L., Fereres, E., 2009. Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle. *IEEE Trans. Geosci. Remote Sens.* 47 (3), 722–738.
- Biggar, S.F., Slater, P.N., Gellman, D.I., 1994. Uncertainties in the in-flight calibration of sensors with reference to high-reflectance ground sites in the 0.4–1.1 μm range. *Remote Sens. Environ.* 48 (2), 245–252.
- Biggar, S.F., Thome, K.J., Wisniewski, W., 2003. Vicarious radiometric calibration of EO-1 sensors by reference to high-reflectance ground targets. *Geosci. Remote Sens., IEEE Trans.* 41 (6), 1174–1179.
- Broge, N.H., Leblanc, E., 2001. Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. *Remote Sens. Environ.* 76 (2), 156–172.
- Chen, X., Zhao, H., Li, P., Yin, Z., 2006. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. *Remote Sens. Environ.* 104 (2), 133–146.
- Chuvieco, E., Huete, A., 2009. *Fundamentals of Satellite Remote Sensing*. CRC Press Inc.
- Davranche, A., Lefebvre, G., Poulin, B., 2009. Radiometric normalization of SPOT-5 scenes: 6S atmospheric model versus pseudo-invariant features. *Photogramm. Eng. Remote Sens.* 75 (6).
- Dinguirard, M., Slater, P.N., 1999. Calibration of space-multispectral imaging sensors: a review. *Remote Sens. Environ.* 68 (3), 194–205.
- Espósito, F., Rufino, G., Moccia, A., 2007. 1st Mini-UAV Integrated Hyperspectral/Thermal Electro-Optical Payload for Forest Fire Risk Management. In: *Proc. AIAA InfotechAerosp. Conf.* pp. 653–665.
- Gilbert, M.A., González-Piqueras, J., García-Haro, F.J., Meliá, J., 2002. A generalized soil-adjusted vegetation index. *Remote Sens. Environ.* 82, 303–310.
- Gilbert, M.A., González-Piqueras, J., Martínez, B., 2011. Theory and application of vegetation indices. In: Maselli, F., Menenti, M., Brivio, P.A. (Eds.), *Optical Observation of Vegetation Properties and Characteristics*. Research Signpost, Kerala, India, pp. 1–43.
- <http://www.gnu.org/software/octave> (accessed 01.12.13).
- Hailey, T.L., 2005. The powered parachute as an archaeological aerial reconnaissance vehicle. *Archaeol. Prospection* 12 (2), 69–78.

- Hernández-López, D., Felipe-García, B., González-Piqueras, J., Alcázar, G.V., 2011. An approach to the radiometric aerotriangulation of photogrammetric images. *ISPRS J. Photogramm. Remote Sens.* 66 (6), 883–893.
- Hernández-López, D., Felipe-García, B., Sánchez, N., González-Aguilera, D., Gomez-Lahoz, J., 2012. Testing the radiometric performance of digital photogrammetric images: vicarious vs. laboratory calibration on the Leica ADS40, a study in Spain. *Photogramm. Fernerkundung Geoinform.* 2012 (5), 557–571.
- Hernandez-Lopez, D., Felipe-Garcia, B., Gonzalez-Aguilera, D., Arias-Perez, B., 2013. An automatic approach to UAV flight planning and control for photogrammetric applications: a test case in the asturias region (Spain). *Photogramm. Eng. Remote Sens.* 79 (1), 87–98.
- Herwitz, S.R., Johnson, L.F., Dunagan, S.E., Higgins, R.G., Sullivan, D.V., Zheng, J., Lobitz, B.M., Leung, J.G., Gallmeyer, B.A., Aoyagi, M., Slye, R.E., Brass, J.A., 2004. Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support. *Comput. Electron. Agric.* 44, 49–61.
- Hiscocks, P.D., 2011. Measuring Luminance with a Digital Camera. <<http://www.ee.ryerson.ca/~phiscock/astronomy/light-pollution/luminance-notes.pdf>> (accessed 17. 07. 14).
- Honkavaara, E., Arbiol, R., Markelin, L., Martinez, L., Cramer, M., Bovet, S., Chandelier, L., Ilves, R., Klonus, S., Marshal, P., Schlöpfer, D., Tabor, M., Thom, C., Veje, N., 2009. Digital airborne photogrammetry—a new tool for quantitative remote sensing?—a state-of-the-art review on radiometric aspects of digital photogrammetric images. *Remote Sens.* 1 (3), 577–605.
- Huete, A.R., 1988. A soil-adjusted vegetation index. *Remote Sens. Environ.* 25, 298–309.
- Kelcey, J., Lucieer, A., 2012. Sensor correction of a 6-band multispectral imaging sensor for UAV remote sensing. *Remote Sens.* 4, 1462–1493.
- Krurup, T., Juhl, J., Kubik, K., 1980. In: *Götterdämmerung Over Least Squares Adjustment*, XIV Congress of International Society of Photogrammetry, Hamburg; Hamburg. pp. 369–378.
- Lass, L.W., Callihan, R.H., 1997. The effect of phenological stage on detectability of yellow hawkweed (*Hieracium pratense*) and oxeye daisy (*Chrysanthemum leucanthemum*) with remote multispectral digital imagery. *Weed Technol.* 11 (2), 248–256.
- NavCen, 2008. Global Positioning System Standard Positioning Service Performance Standar, 4th ed. US Department of Defense: Position, Navigation, and Timing Executive Committee, Washington, DC.
- Pope, A.J. 1976. The statistics of residuals and the detection of outliers. In: NOAA Technical Report NOS 65 NGS 1, National Ocean Service, National Geodetic Survey. US Department of Commerce, Rockville, MD, Washington, 133pp.
- Premierani, W., Bizard, P., 2013. Direction Cosine Matrix IMU: Theory. <<http://gentlenav.googlecode.com/files/DCMDraft2.pdf>> (accessed 01.12.13).
- Qi, J., Chehbouni, A., Huete, A., Kerr, Y., Sorooshian, S., 1994. A modified soil adjusted vegetation index. *Remote Sens. Environ.* 48 (2), 119–126.
- Reda, I., Andreas, A., 2004. Solar position algorithm for solar radiation applications. *Sol. Energy* 76 (5), 577–589.
- Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., Harlan, J.C., 1974. Monitoring the vernal advancement of retrogradation of natural vegetation, NASA/GSFC, Type III. In: Final Report. Greenbelt, MD, p. 371.
- Schmidt, K.S., Skidmore, A.K., 2003. Spectral discrimination of vegetation types in a coastal wetland. *Remote Sens. Environ.* 85 (1), 92–108.
- Takasu, T., 2009. RTKLIB: Open Source Program Package for RTK-GPS. FOSS4G, Tokyo, Japan.
- Turner, D., Lucieer, A., Watson, C., 2011. Development of an Unmanned Aerial Vehicle (UAV) for hyper resolution vineyard mapping based on visible, multispectral, and thermal imagery. In: Proceedings of 34th International Symposium on Remote Sensing of Environment. p. 4.
- Vermote, E.F., Tanre, D., Deuze, J.L., Herman, M., Morcette, J.J., 1997. Second simulation of the satellite signal in the solar spectrum, 6S: an overview. *IEEE Trans. Geosci. Remote Sens.* 35 (3), 675–686.
- Xiang, H., Tian, L., 2007. Autonomous Aerial Image Georeferencing for an UAV-Based Data Collection Platform Using Integrated Navigation System. ASABE Annual Meeting, Minneapolis, Minnesota.
- Zarco-Tejada, P.J., Miller, J., Morales, A., Berjón, A., Agüera, J., 2004. Hyperspectral indices and model simulation for chlorophyll estimation in open-canopy tree crops. *Remote Sens. Environ.* 90 (4), 463–476.
- Zhang, C., Kovacs, J., 2012. The application of small unmanned aerial systems for precision agriculture: a review. *Precision Agric.* 13 (6), 693–712.
- Zhao, W.T., Peng, J.Y., 2006. VORONOI diagram-based path planning for UAVs. *J. Syst. Simul.* 18 (2), 159–162.
- Zheng, Y., Lin, S., Kambhamettu, C., Jingyi, Y., Sing Bing, K., 2009. Single-image vignetting correction. *IEEE Trans. Pattern Anal. Mach. Intell.* 31, 2243–2256.

3.2. Estimación del rendimiento de los viñedos a través de la modelización automática en 3D de los racimos en condiciones de campo

El objetivo de este artículo consiste en el desarrollo de un método capaz de determinar la productividad del viñedo de una manera novedosa en el sector, garantizando flexibilidad y sencillez en la toma de datos, automatismo en el proceso, calidad en los resultados y un bajo coste asociado. La tecnología idónea en el ámbito de la viticultura de precisión es la combinación de la calidad de los métodos numéricos fotogramétricos con la flexibilidad, automatismo y rapidez de los métodos procedentes de la visión computacional. Es por ello por lo que se opta por una técnica de modelado 3D a partir de imágenes que se logra mediante dos pasos principales: la determinación automática de la vista de cada imagen y el cálculo automático de las coordenadas 3D para la generación de un modelo 3D denso y escalado de la escena. Esta tecnología no destructiva ni invasiva con un bajo coste asociado, permite la adquisición de datos de forma remota a una gran velocidad consiguiendo características geométricas y texturales de los objetos con un elevado grado de precisión y detalle en escenarios complejos, por encima incluso de los costosos sistemas láser (Lumme, 2008) y de las tecnologías gaming sensor que muestran dificultades en escenarios externos con luz diurna (Lange, 2011) teniendo además una estricta limitación en la distancia de alcance. Con ello se pretende desarrollar un proceso que permita medir el rendimiento del viñedo a nivel de racimo.

Para ello, se reconstruye métricamente racimos en 3D a partir de imágenes tomadas procesadas con el software Photogrammetry Workbench (PW) (González-Aguilera et al., 2013). El descriptor robusto que proporciona mejores resultados en este estudio es la variación SIFT (ASIFT), donde las variaciones en la geometría y la iluminación son muy comunes. Además, se integran varios modelos de calibración de la cámara como el modelo de Brown o el modelo de Fraser para permitir trabajar con cualquier tipo de cámara, incluyendo teléfonos inteligentes de bajo coste y tablets (Akca y Gruen, 2007). Dicho software consigue hacer frente a limitaciones fotogramétricas como son: primero, el autocalibrado la cámara durante el propio proceso de cálculo (Quan, 2010); segundo la incorporación de algoritmos de auto-escalado basados en el conocimiento de la base línea entre las imágenes o en el reconocimiento de tarjetas o dispositivos de escalado específicos; tercero, la flexibilidad de la toma fotográfica al permitir trabajar con

cualquier tipo de cámara incluso los dispositivos de tecnología moderna como smartphones y tablets (Akca & Gruen, 2007).

La medición del rendimiento del viñedo se determina mediante una serie de componentes de producción, como son el volumen, masa y número de bayas del racimo (Greven, 2007). En este estudio se trata de establecer estas componentes, demostrando así la viabilidad de escalar la metodología propuesta a la estimación de la producción total del viñedo ($\text{kg}\cdot\text{m}^{-2}$). Se mejoraría la estimación de los métodos actuales como son las relaciones empíricas propuestas por Greven (2007) o los métodos clásicos o alternativos (Kurtural, 2007). Por ello, se han implementado diferentes algoritmos que logran analizar dimensionalmente los racimos a partir de la nube de puntos métrica, siguiendo dos estrategias de cálculo que se apoyan en diferentes técnicas de modelización de la nube de puntos 3D del racimo. El primero se trata de un procedimiento automático de cálculo sustentado en generar la envolvente convexa (O'Rourke, 1994) de la nube de puntos 3D de la cara vista del racimo. La segunda estrategia se basa en un procedimiento semi-automático sustentado en procesos de ingeniería inversa que permite generar objetos CAD (Computer Asisted Design) a partir de nubes de puntos 3D (DeLuca et al., 2006), mediante la aproximación de Attene (2010).

La toma de datos se realizó en octubre del 2013 en un viñedo experimental de secano de Tempranillo (*Vitis vinifera* L.) de 1.05 hectáreas, situado a 6 km de Logroño. Los componentes de rendimiento reales se establecieron mediante ensayos de laboratorio de inmersión (cálculo del volumen), pesado y conteo individual de las bayas de cada racimo de estudio. Esta verdad terreno se contrastó con los parámetros estadísticos calculados adquiriendo el error de cada estimación. Posteriormente, se eliminaron los errores groseros detectados mediante el test de Pope (Pope, 1976). Por último, se estableció una correlación lineal entre los parámetros estimados y reales, obteniendo un coeficiente de determinación medio de las diferentes variables de producción en ambas aproximaciones de 0.77. Tras este análisis, es posible afirmar que el proceso semi-automático no aporta mejoras significativas, optando por el acercamiento automático, en el que el tiempo de procesamiento es menor y no requiere operadores humanos con lo que se disminuye notablemente la variabilidad subjetiva así como el coste asociado.

Los resultados obtenidos confirman la viabilidad del método, ofreciendo escalabilidad a un análisis exhaustivo de la productividad de la explotación y facilitando una mejora operativa constante así como una gestión proactiva.

Palabras clave: *estimación del rendimiento, fotogrametría, vision computacional, Vitis vinifera L, automatización, tecnologías no invasivas.*



Vineyard yield estimation by automatic 3D bunch modelling in field conditions



Mónica Herrero-Huerta^{a,*}, Diego González-Aguilera^a, Pablo Rodríguez-Gonzálvez^a,
David Hernández-López^b

^a Department of Cartographic and Land Engineering, University of Salamanca, Higher Polytechnic School of Avila, Hornos Caleros 50, 05003 Avila, Spain

^b Institute for Regional Development (IDR), University of Castilla La Mancha, 02071 Albacete, Spain

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ABSTRACT

This manuscript focuses on developing a workflow for determining the productivity of vineyards in a novel and innovative way, ensuring flexibility and simplicity in data acquisition, automation in the process and high-quality results, using low cost sensors. The non-invasive system proposed allows the determination of yield at cluster level by combining close-range photogrammetry and computer vision. Bunches are reconstructed in 3D from images processed with Photogrammetry Workbench software (PW) developed by the authors. Algorithms and techniques were combined to estimate the most relevant parameters in the productivity of a vineyard: volume, mass and number of berries per bunch. To validate the workflow proposed, a sample of laboratory tests based on dimensional analysis of the clusters together with the single count of berries, were analyzed to establish the groundtruth. The results achieved from the scaled models and different estimation parameters were contrasted. The results confirm the feasibility of the proposed methodology, providing scalability to a comprehensive analysis of the productivity of the vineyard and affording a constant operational improvement and proactive management.

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1. Introduction

The development of innovative technologies in viticulture to monitor vineyards is encouraged because of their huge environmental and economic impact on society. Computer vision systems are highly suitable for this purpose because they are a non-contact and non-destructive technique (Chherawala et al., 2006). The application scenarios of digital image analysis cover yield estimation, quality evaluation, disease detection and grape phenology (Whalley and Shanmuganathan, 2013). One of the main concerns in the wine industry along history has been the accurate and objective estimation of the yield and the oenological potential of vineyards: *yield forecasting* or *harvest forecasting*. Currently, this is still an unresolved issue and is of great technical and economic importance (Wolpert and Vilas, 1992; Clingeffer et al., 2001; Dunn and Martin, 2004). A precise vineyard yield estimation allows more efficient grapevines to be obtained, their qualitative potential to be established, and the production of higher-quality wines (Dunn and Martin, 2003). Roby et al. (2004) checked that

berry size is a determining factor for winegrape quality where the berry small size is related to lack of water and the variation in berry size indicates an inhomogeneous maturation. Also, this estimation influences decision-making techniques, such as the execution of vineyard score sheets.

Currently, the methods applied at industrial scale to estimate the productivity of vineyards are destructive, labour- and time-demanding (Martin et al., 2003) and, therefore, economically non-viable. Furthermore, several methods are based mostly on a visual inspection of the vineyard so the final data cannot guarantee reliability and accuracy. In light of this, a specific software (Grape Forecaster) was developed (Martin et al., 2003) to calculate the final harvest, allowing only historical information on yield components and variations from year to year to be collected. Blom and Tarara (2009) proposed a method based on the tension of the wires of the conduction system, which is expensive. Grape yield assessment was studied from the point of view of water availability and its effects on yield and berry quality attributes (Serrano et al., 2012) by expensive measuring techniques. For these reasons, in recent years image analysis has begun to be applied in viticulture in attempts to assess the vegetative state or performance of vineyards in some countries such as Australia

* Corresponding author. Tel.: +34 920353500x3820.

E-mail address: monicaherrero@usal.es (M. Herrero-Huerta).

(Dunn and Martin, 2004) or the U.S. (Nuske et al., 2011). More concretely, Dunn and Martin (2004) captured in field images using a white screen behind the canopy and extracted the colour features to classify the berry clusters, using manual thresholds and tolerances for the segmentation. The work of Nuske et al. (2011) involves a visible light camera boarded in a small vehicle to survey the entire vineyard. The berries are detected based on a 2D radial symmetry transform to extract their center, and then are classified based on their colour and texture. Finally a clustering is applied to remove false positives. In a recent work (Nuske et al., 2012) the use of calibration data from prior harvest data enhanced the previous results. Moreover, 2D computer vision techniques have also been applied to individual strains for the identification of plant elements (Herrero Langreo et al., 2010) or counting individual berries using a flatbed scanner (Battany, 2008). A 2D grapevine yield and leaf area estimation was done by Diago et al. (2012), who used a visible light camera to capture images in-field using a white screen behind the canopy. Their approach involves the computation of Mahalanobis colour distance for a supervised classification application. Approaches to obtaining 3D models from photographs for plant analyses were carried out at a laboratory with individual tomato plants (Aguilar et al., 2008), but without effective automation and failing to translate this technology to field conditions. More recently, Djuricic et al. (2014) employed an active sensor, multi-echo laser scanner, for grape berries detection, through the laser intensity.

This paper aims to establish a method for estimating vine production in field conditions using low-cost, non-invasive methods based on computer vision (Sethian, 1999). Thus, 3D models of bunches were obtained and dimensional analyses were carried out to calculate the different yield components. The development of the proposed method had to face additional difficulties, such as the partial 3D models generated by *in-situ* bunch documentation (only the visible side of the bunch), or having to deal with the occlusions and geometrical complexities of the strain itself. Techniques and algorithms to estimate the components of vineyard yields were developed. The recovery of the non-visible side in the model was achieved using convex hull techniques (Barber et al., 1996). The main output of this workflow was an accurate and precise predictive method aimed at eliminating the subjectivity deriving from the spatial and temporal variability of grape production. This would allow vine growers to take decisions in advance.

2. Image-based modelling

For precision agriculture purposes, a combination of Photogrammetry quality and computer vision algorithms (flexibility, automation and efficiency) is required. An image-based modelling technique based on this combination allows 3D models to be obtained from 2D images via two main steps: first, the automatic determination of the view of each image taken at vineyards; second, the automatic computation of the 3D coordinates for the generation of a dense and scaled 3D model of the scene.

This is a non-destructive and non-invasive technology with low associated costs. The methodology allows data to be acquired remotely with great efficiency, affording the radiometric and geometric characteristics of objects with a high degree of accuracy and detail in complex scenarios. Moreover, photogrammetry has advantages over others sensors, such as expensive laser systems (Lumme et al., 2008) or gaming sensor technologies, which are subject to difficulties in external daylight scenarios (Lange et al., 2011) as well as having a reduced working range.

To develop the proposed method, several robust descriptors for feature extraction and matching were implemented and tested, the SIFT variation (ASIFT) being the one that provided the best results in this study, where variations in geometry and lighting were very

common. Last, but not least, several camera calibration models, such as the Brown model or the Fraser model, were integrated to allow working with any type of camera, including low-cost smartphones and tablets (Akca and Gruen, 2007).

Fig. 1 schematizes the workflow of the PW software (González-Aguilera et al., 2013) based on image-based modelling.

2.1. Image acquisition protocol

The image acquisition protocol is the key to success of the developed process since these images represent the input data of the workflow, and thus their position (spatial and attitude) will affect the final accuracy (i.e. in terms of perspective ray intersection) and completeness (i.e. in terms of overlap between images) of the 3D model.

Prior to image acquisition, the scene must be analyzed, including the lighting conditions because these will influence the exposure values, and the aperture and shutter speeds of the sensor. To this end, images should be acquired without strong variations in illumination, avoiding overexposed areas and ensuring sharpness, together with an occlusion analysis due to the presence of obstacles that will affect the image acquisition protocol and the overlaps between adjacent images. The shortest available focal length of the camera should be chosen and must be held constant throughout the image acquisition process to keep the internal camera parameters stable.

Regarding the geometric conditions of the camera shots, the objective is to establish an image acquisition protocol to reconstruct the grapevine of interest, guaranteeing the completeness and best accuracy of the resulting 3D model to perform the dimensional analysis of each cluster. It should be remarked that finding an optimal image network can be complex, in particular in scenes with strong depth variations and occlusions. Therefore, the key at this point is to establish a guideline, based on simple geometric constraints, to perform image acquisition at vineyards (Fig. 2). For an extensive vineyard study, at least five images (one master and four slaves) must be taken of each grapevine. The master image should cover the study grapevine and represents the origin of the coordinate system. This image has to be taken in a frontal way and framing the principal part of the grapevine or, if possible, including all of it. The overlaps between the slaves and master image must be high (80–90%) and must always maintain a slight convergence (i.e. optical axis) (maximum 15°) so that image matching will be ensured during the orientation phase. Regarding depth, this should be chosen according to the image scale or the desired resolution. This image acquisition protocol ensures the completeness and quality of the final model.

The automatic scaling of the 3D point clouds is resolved by incorporating self-scaled algorithms based on the automatic recognition of targets of known dimension which should appear in the photograph.

2.2. Features extraction and matching

One of the most critical steps in this process is the extraction and matching of features (lines and points) with high accuracy and reliability. This constitutes the framework that supports the whole process by providing the necessary information to resolve the spatial and attitude positions of images (orientation), camera self-calibration and, finally, grapevine 3D reconstruction. In addition, agricultural scenes usually show variations in scale, perspective and illumination, so classical descriptors based on grey levels such as area-based matching (ABM) (Joglekar and Gedam, 2012) and least square matching (LSQ) (Gruen, 1985) are useless. To this end, more sophisticated and robust descriptors were tested: smallest univalue segment assimilating nucleus (SUSAN)

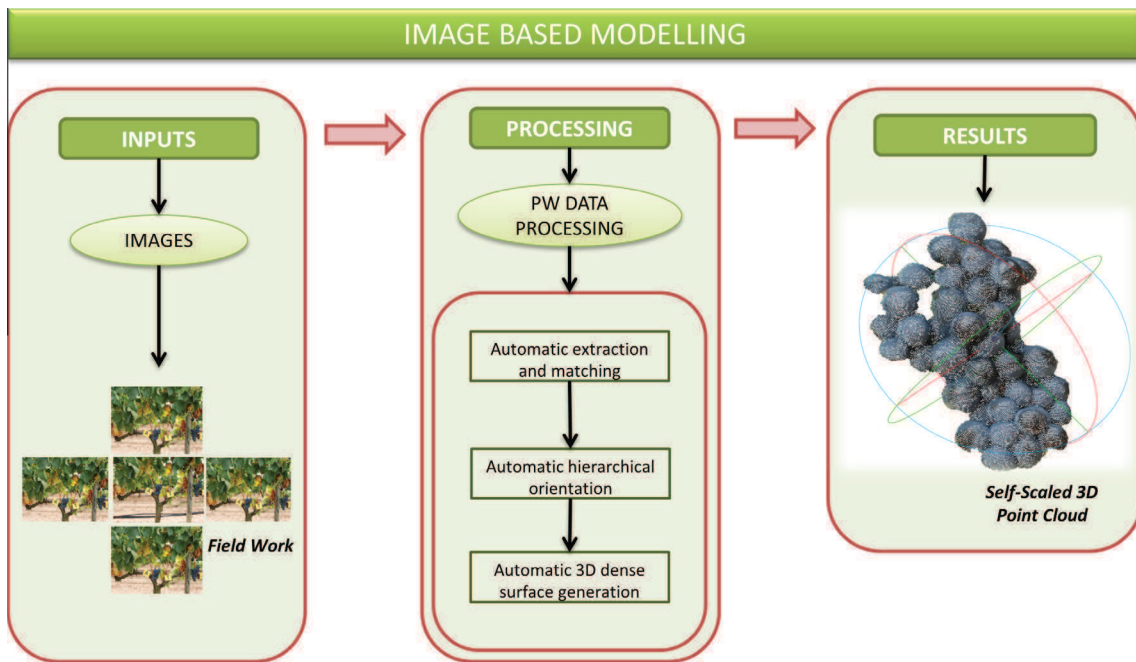


Fig. 1. Workflow of image-based modelling technique.

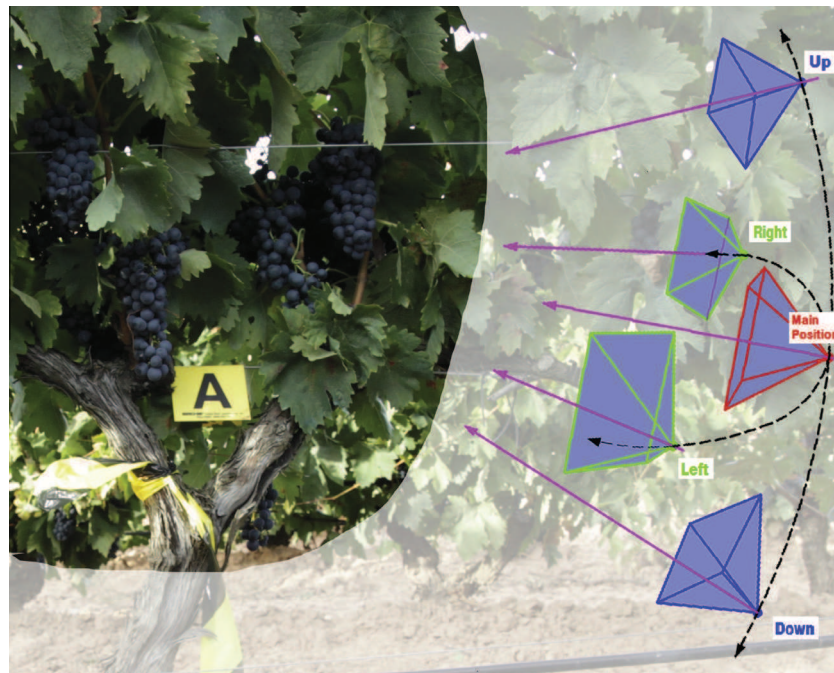


Fig. 2. Protocol of image acquisition of the study grapevines.

(Smith and Brady, 1997); scale invariant feature transform (SIFT) (Lowe, 2004); maximally stable extremal regions (MSER) (Matas et al., 2004) and speeded up robust features (SURF) (Bay et al., 2006). Unfortunately, all these algorithms become ineffective when there are considerable variations in perspective between images.

In this sense, a variation of the SIFT algorithm, called affine scale invariant feature transform (ASIFT) (Morel and Yu, 2009), has been incorporated to the PW software. It permits the consideration of two additional affinity parameters that control the perspective of the images. These are the angles corresponding to two perspective angles of the camera's optical axis, the ϖ angle (tilt) and the φ

angle (axis) (Eq. (1)). In this way, the ASIFT algorithm allows one to cope with images that have a high degree of perspective, which is very common in vineyards. The result is an invariant descriptor that considers scale, rotation, movement and significant deformations due to the perspective between images. This result provides the next expression:

$$\begin{aligned}
 A &= \begin{bmatrix} a & b \\ c & d \end{bmatrix} = H_i R_1(\kappa) T_1 R_2(\varpi) \\
 &= \lambda \begin{bmatrix} \cos \kappa & -\sin \kappa \\ \sin \kappa & \cos \kappa \end{bmatrix} \cdot \begin{bmatrix} t & 0 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \cos \varpi & -\sin \varpi \\ \sin \varpi & \cos \varpi \end{bmatrix} \quad (1)
 \end{aligned}$$

where A is the affinity transformation that contains the scale (λ), rotation (κ) around the optical axis (swing) and perspective parameters corresponding to the inclination of the camera optical axis (φ (tilt)), the vertical angle between the optical axis and the line perpendicular to the image plane and the horizontal angle between the optical axis and the fixed vertical plane (ϖ (axis)).

The matching process is carried out by SIFT descriptors. These descriptors are first matched according to the Euclidean distance (Lowe, 1999), after which they are filtered by the optimized random sampling algorithm (ORSA) (Moisan and Stival, 2004; Moisan et al., 2012). This algorithm is a variant of random sample consensus (RANSAC) (Fischler and Bolles, 1981) with an adaptative criterion to filter outliers by epipolar geometry constraints.

2.3. Hierarchical image orientation

Computing the spatial and attitude position of images is not an easy mathematical task. Furthermore, image orientation is based on features related to extraction and matching, so the presence of outliers could be quite common. In this sense, the method proposes a hierarchical approach for obtaining an approximate and relative image orientation in an arbitrary coordinate system based on computer vision. It can be refined and improved in an absolute and scaled coordinate system for the set of images thanks to photogrammetry.

Firstly, a relative image orientation is achieved using independent models obtained from the fundamental matrix calculated with the Longuet-Higgins algorithm (Longuet-Higgins, 1987). One of the greatest advantages of the fundamental matrix is that it is independent of any scene, so no knowledge of the internal parameters or initial approaches of the camera is required.

Secondly, once the relative attitude and spatial position of images has been obtained, a global adjustment of all images (bundle-adjustment) is performed by an iterative and least-squares process based on the collinearity condition (Kraus, 1993). The coordinates of the ground control points are incorporated for absolute georeferencing (Eq. (2)). These ground coordinates are added to the orientation process as artificial targets located around the vineyard. In cases in which the internal calibration parameters of the camera are unknown (principal distance, principal point and lens distortion), this second step allows these parameters (self-calibration) to be incorporated into the equation as unknowns (Quan, 2010).

$$\begin{aligned} (x - x_0) + \Delta x &= -f \frac{r_{11}(X - S_x) + r_{21}(Y - S_y) + r_{31}(Z - S_z)}{r_{13}(X - S_x) + r_{23}(Y - S_y) + r_{33}(Z - S_z)} \\ (y - y_0) + \Delta y &= -f \frac{r_{12}(X - S_x) + r_{22}(Y - S_y) + r_{32}(Z - S_z)}{r_{13}(X - S_x) + r_{23}(Y - S_y) + r_{33}(Z - S_z)} \end{aligned} \quad (2)$$

where x, y are the image coordinates of a point of the scene; X, Y, Z are the coordinates of the scene point expressed in a local reference system; r_{ij} are the rotation matrix coordinates; S_x, S_y, S_z are the spatial coordinates of the camera point of view; f is the camera focal length; x_0, y_0 are the principal point coordinates of the image, and X, Y are the radial and tangential distortion parameters of the lens.

2.4. Automatic dense surface generation

Starting from the robust image orientation, a dense matching process was developed. It is based on the semi-global matching technique (SGM) (Hirschmuller, 2005; Deseilligny and Clery, 2011). Applying the projective equation (Hartley and Zisserman, 2003) (3), it permits the generation of a dense model resulting from the determination of a 3D coordinate per pixel.

$$x_k = C(D(R_i(X_k - S_i))) \quad (3)$$

where X is the 3D point; x is the point corresponding to the image; R is the camera rotation matrix; S is the camera projection center; C is the internal calibration function; D is the lens distortion function, and the subscripts k and i are related to point and image, respectively.

The SGM process consists of minimizing an energy function (4) through the eight basic directions that a pixel can take. This function is composed of a cost function, M , which reflects the degree of similarity of the pixels between two images, x and x' , together with the incorporation of two restrictions, and P_1 and P_2 , which show the possible presence of outliers in the SGM process.

$$\begin{aligned} E(D) &= \sum_x (M(x, D_x) + \sum_{x' \in N_x} P_1 T[|D_x - D_{x'}| = 1] \\ &\quad + \sum_{x' \in N_x} P_2 T[|D_x - D_{x'}| > 1]) \end{aligned} \quad (4)$$

where $E(D)$ is the energy function to be minimized on the basis of the disparity between the homologous characteristics; the function C evaluates the level of similarity between the pixel p and its counterpart q through the disparity D_p , while the P_1 and P_2 terms correspond to two restrictions to avoid outliers in the dense matching process due to the disparity of one pixel or a higher number of them, respectively.

In addition, a third constraint was added to the SGM process. This consisted of epipolar geometry derived from photogrammetry (Hartley and Zisserman, 2003) and can enclose the search space per pixel in order to reduce the huge computational cost. In particular, based on the computed fundamental matrix, F , the following search band is defined: $l' = xF$, which establishes that the corresponding point of x should be along the epipolar line l' . In other words if two image points (x and x') correspond, then the epipolar line l' is defined $l' = Fx$. As a result, it will generate a dense model with multiple images, obtaining more optimal processing times.

3. Estimation of vineyard yields

The measurement of vineyard yields is accomplished with a set of production components, such as volume, mass and the number of berries per bunch (Greven, 2007). This study attempts to establish these components, demonstrating the feasibility of scaling the proposed methodology to the total yield estimation of the vineyard ($\text{kg} \cdot \text{m}^{-2}$). The current method improves classic and alternative methods (Kurtural and ÖDaniel, 2007) and the empirical relations proposed by Greven (2007). Different algorithms were implemented to analyze clusters from the metric point cloud dimensionally, obtaining the volume and weight, as well as determining the number of berries, following two computational strategies, as shown in Fig. 3. The first one is automatic and relies on the point cloud generated. The second one is a semi-automatic process and requires computer-aided design (CAD) models from the point cloud.

Both strategies are fed by external variables, the average volume of the berries (V_m) and the average density of the bunches (D_m) calculated by averaging the data acquired in laboratory tests. These variables depend on the area and year of the crop.

$$V_m = \frac{\sum_{i=1}^{i=n} (V/B)i}{n} \quad (5)$$

$$D_m = \frac{\sum_{i=1}^{i=n} (W/V)i}{n} \quad (6)$$

where V_m is the average berry volume calculated by means of the real bunch volume (V), the number of bunches (n) and the real number of berries per bunch (B); D_m is the average density of the bunch, and W is the real weight of the bunch.

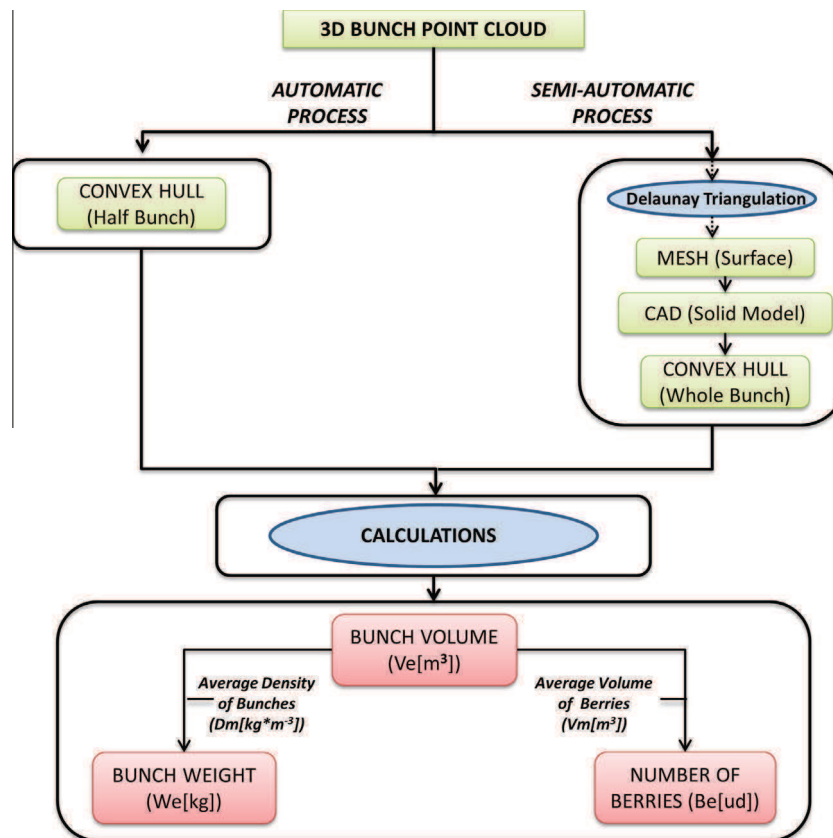


Fig. 3. Different computational strategies of vineyard production components from 3D bunch point cloud.

The two methods described are based on different modelling techniques of the 3D point cloud of the cluster. The first one is an automatic process supported by generating the convex hull (O'Rourke, 1994) of the 3D point cloud of the visible side of the cluster. This volume limited by the hull (V_c) collects half of the whole cluster due to the field of view of the camera and the limitations of the branches and leaves, closing the hidden side of the cluster by a flat surface. Because the convex hull includes empty spaces where there are no berries, as well as the exclusivity of the visible side of the bunch it is necessary to include an empirical correction factor (K) (Nuske et al., 2011; Nuske et al., 2012) that will refine the estimated volume (V_e).

The second strategy is based on a semi-automatic process supported by reverse engineering procedures that allows CAD models to be generated from 3D point clouds (DeLuca et al., 2006). It is noteworthy that there are still serious barriers in our knowledge of full automation in the conversion to CAD solid models, especially in the case of complex objects (Gonzalez-Aguilera et al., 2012). This approach requires the triangulation of the point cloud from the cluster to achieve the spatial topology required to model it. The meshing algorithm chosen was 3D Delaunay triangulation (Galias and Dutton, 1997) to obtain a TIN (Triangle Irregular Network). With this approach, the volume enclosed by the convex hull (V_c) of the whole cluster can be achieved, from modelling the individual berries of the visual side of the bunch and the subsequent symmetry. As in the automatic approach, an empirical correction factor (K) that refines the estimated volume (V_e) is required.

Fig. 4 shows both computational processes.

This second approach is more tedious. To obtain a CAD model close to reality, the mesh has to be repaired previously. This step uses the approximation of Attene (2010), which incorporates several automatic and sequential tasks:

- Filling of holes through algorithms of planar triangulations (Barequet and Sharir, 1995) or more complex approaches based on interpolators of radial basis function (Branch et al., 2006), the minimum distance (Dolenc and Makela, 1993) and the measurement of angles (Bohn and Wozny, 1992; Varnuška et al., 2005).
- Repair of meshing gaps, based on minimum threshold distance algorithms (Rock and Wozny, 1992; Barequet and Kumar, 1997).
- Removal of topological noise, allowing the mesh to be re-triangulated locally (Guskov and Wood, 2001).
- Removal of geometric noise by algorithms that apply filters as anti-aliased Laplacians in general or specific zones (Fan et al., 2008).

After this reconstruction, the mesh has been modelled to obtain a solid CAD comprising two stages: segmentation and adjustment of basic primitives. As proposed by Wang et al. (2012), the segmentation process involves 3 steps:

- Plane segmentation using the region growing technique.
- Segmentation of quadric surfaces from knowledge of the vertex curvature obtained by fitting the local vicinity (Besl and Jain, 1988).
- Segmentation of free surfaces relying on the region growing technique to maximize the number of vertices connected topologically that can be generalized as a free surface of the B-spline type.

Once the geometry has been segmented, modelling continues with the setting of basic primitives. Thus, berries were approximated to spheres, extracted by an iterative adjustment of the minimization of the Euclidean distance from the mesh.

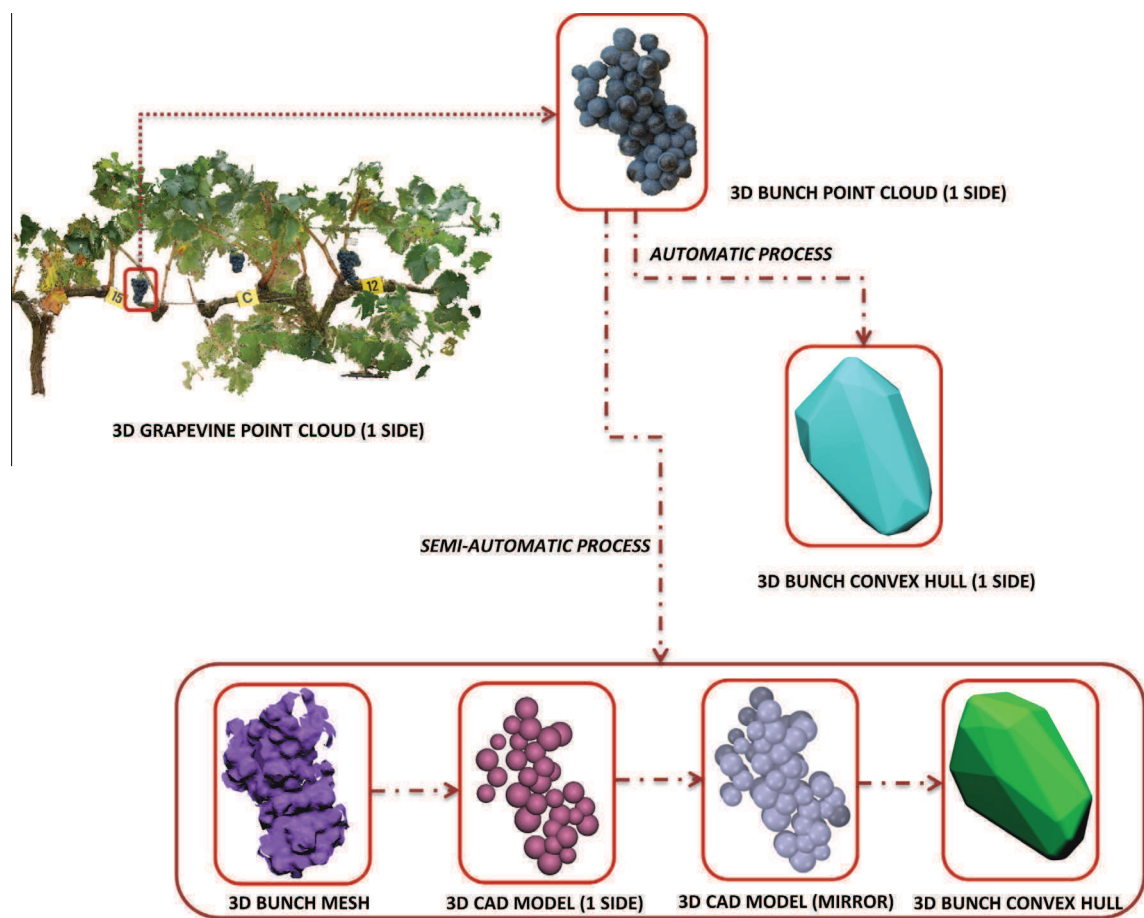


Fig. 4. Workflow of different computational processes to obtain the convex hull of the cluster.

The mathematical models implemented in both approaches are detailed below, where Eq. (7) shows the bunch volume estimated (Ve); bunch weight is estimated (We) in Eqs. (8) and (9) calculates the number of berries estimated per bunch (Be). Vc represents the volume limited by the convex hull and K is the empirical correction factor:

$$Ve = Vc * K \tag{7}$$

$$We = Vc * K * Dm \tag{8}$$

$$Be = Vc * K / Vm \tag{9}$$

Finally, a correlation between the calculated components and the groundtruth by a sampling of laboratory tests was established to analyze and validate the results acquired with both strategies.

4. Experimental results

Data collection was performed on the 20th of October 2013, on a day with bright and homogeneous lighting, at an experimental dry-farmed cv. Tempranillo (*Vitis vinifera* L.) vineyard of 1.05 ha, located 6 km from Logroño (lat. 42°26' N; long. 2°30' W; 455 m asl, La Rioja, Spain). Many studies have been conducted previously at this location (Romero et al., 2010; Vicente Renedo et al., 2007).

Tempranillo vines (clon RJ-26) were grafted onto Richter-110 rootstock and planted in 1995, following a between-row and within-row spacing of 2.90 m × 1.15 m respectively, with an East–West orientation. This corresponds to a density of 2998 vines/ha. The grapevines were spur-pruned on a bilateral cordon and trained to a VSP trellis system. The trellis featured a



Fig. 5. Image of trellis vineyards selected for this study.

Table 1
Technical specifications of the photographic sensor.

Canon EOS 500D	
Type	CMOS
Sensor size	22.3·14.9 mm
Total pixels	15.1 Mpixels
Image size	4752·3168 pixels
Focal length	17 mm

supporting wire at 0.70 m, two wires at 1.00 m above the ground for protection against wind damage, and a pair of movable shoot-positioned wires at 1.45 m.



Fig. 6. Example of matching points between images.

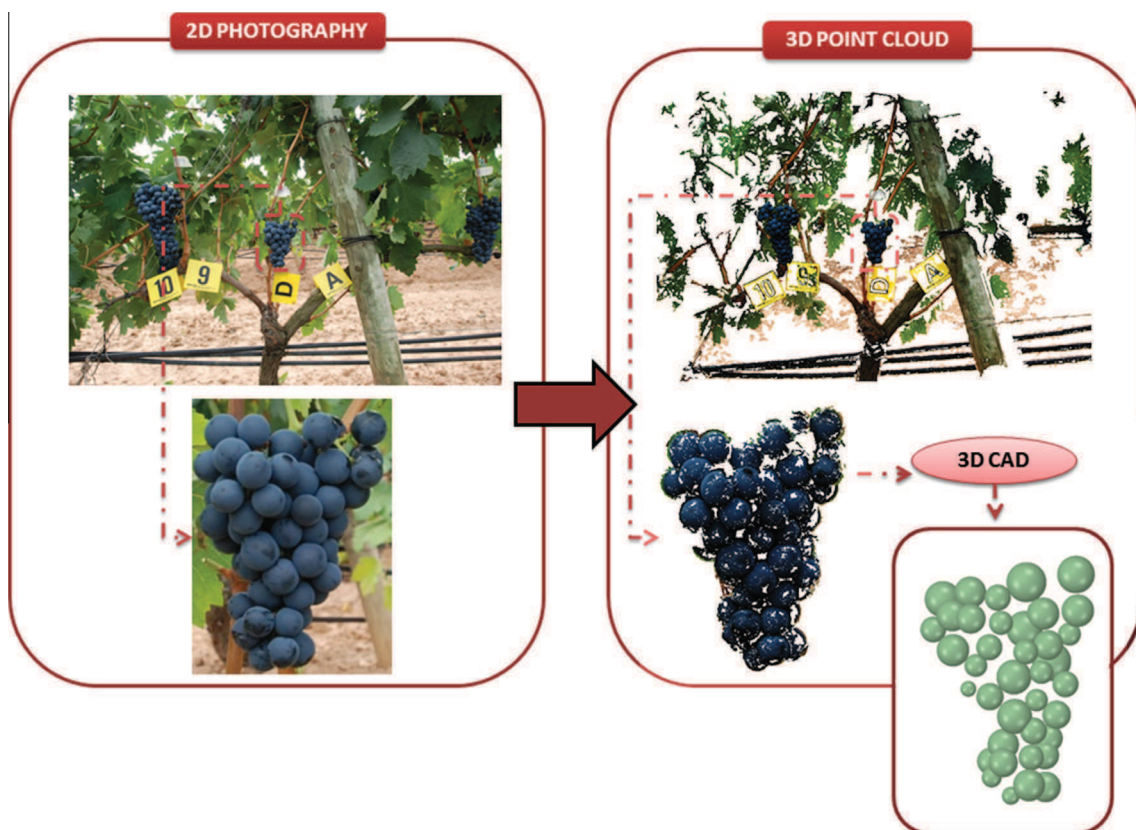


Fig. 7. 3D point cloud and CAD model of a cluster example from 2D images.

To validate the proposed method, 20 clusters from 14 trellis vines were chosen, taking photographs according to the protocol defined in Section 2.1. The selected strains were lightly defoliated to allow one side of the study clusters to be seen. Before taking the photographs, several artificial yellow targets were placed on the ground to allow the automatic scaling of point clouds (Fig. 5).

The main features of the camera used are shown in Table 1:

Images were taken using a fixed short focal length, with an $f/5.6$ aperture, an exposure time faster than $1/160$ s, ISO quality of 200 to decrease image noise, and without flash, owing to the shadow effects. The distance to the grapevine was approximately 2 m in order to maintain it inside the camera depth of field (DOF). The aperture was chosen to achieve an optimal compromise between exposure time, resolution and the DOF.

Photograph acquisition at such close distances requires the consideration of lens parameters, such as the Modulation Transfer

Function (MTF), so the strains were centered in the image to achieve better resolution. Additionally, the MTF was taken into account for lens aperture selection (the lens “sweet” spot).

3D point cloud generation involves the identification and matching of homologous points between images, exemplified in Fig. 6 by straight white lines. The average number of homologous points between pairs of images was 580, obtained automatically through Micmac algorithm (Deseilligny and Clery, 2011). One of the keys to success in the matching process passes through acquiring pair of images with small baseline and thus guarantying high overlap between images. Moreover, the ORSA algorithm used in the matching process consists in introducing an *a contrario* (Desolneux et al., 2000) criterion to avoid the hard thresholds for inlier/outlier discrimination. Thus, the ORSA algorithm finds the right balance between the critical parameter σ and number of inliers by controlling the number of false alarms (Moisan et al., 2012).

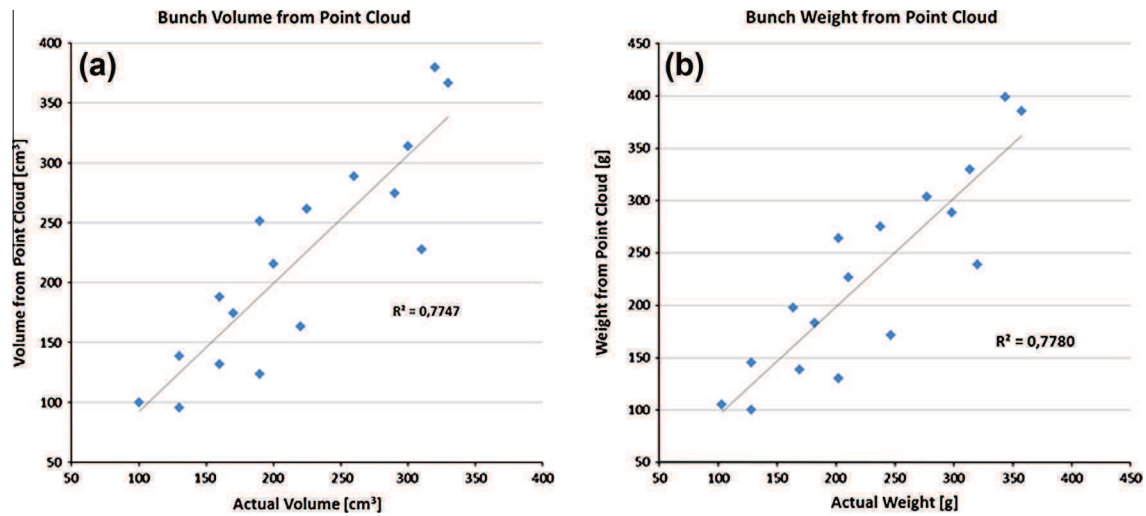


Fig. 8. Bunch volume (a) and weight (b) obtained automatically from point cloud.

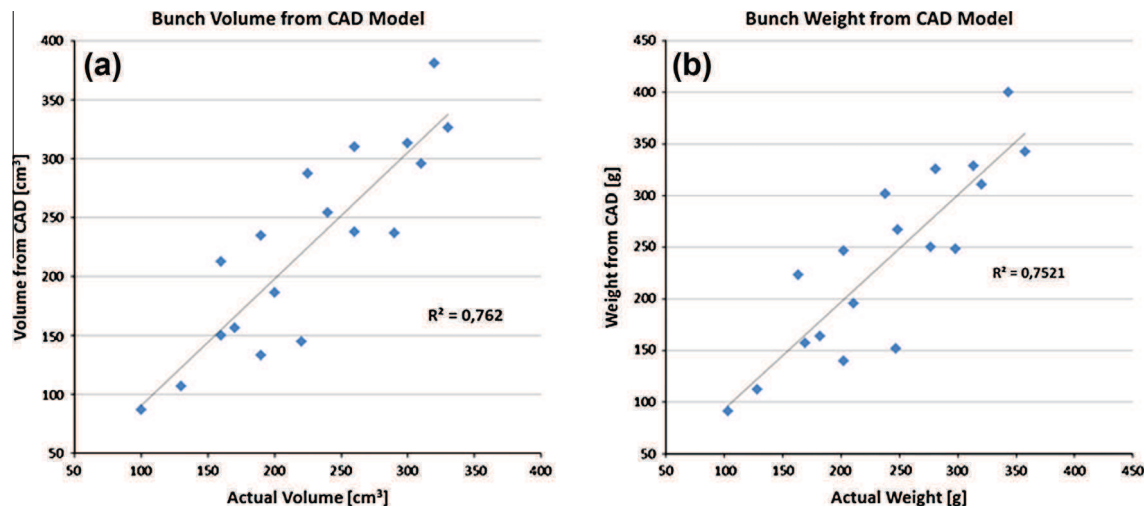


Fig. 9. Bunch volume (a) and weight (b) obtained semi-automatically from CAD model.

The dense point clouds generated have 4,276,000 points per vineyard, while the clusters alone have 96,460 points (as mean value). These points are utilized to create the bunch mesh, having 90,779 points with a ground sample distance of 0.3 mm and a size of 8.3 kB (as mean value).

Fig. 7 shows scaled 3D models of a cluster example and CAD solids through 2D images, which were the inputs of the method proposed to estimate the vineyard yield.

The actual yield components were established by a laboratory test: volume calculation (immersion), weighing, and individual counting of berries per cluster. These laboratory tests which perform as a groundtruth were contrasted with estimated parameters, providing the error of each estimation. Owing to the nature of point clouds, the robust statistical parameter for defining the adjustment is MAD (median absolute deviation) (Mosteller and Tukey, 1977; Sachs, 1984) with respect to the median of the estimated values. Additionally, the Pope test (Pope, 1976) was applied for the detection and removal of the outliers. The final results are shown in Figs. 8–10.

- A coefficient of determination of 0.77 was achieved by comparing the actual volume of the cluster versus the volume

estimated from the point cloud (Fig. 8a). The MAD had a value of 34 cm³ when the median of the estimated volumes was 216 cm³. In the case of bunch weight, an average coefficient of determination of 0.78 g was obtained (Fig. 8b), with a MAD of 35 g when the median was 227 g.

- On comparing the actual volume of the bunch with the estimated volume from CAD modelling, a coefficient of determination of 0.76 was obtained (Fig. 9a). The MAD was 33 cm³, the median taking a value of 236 cm³. When bunch weight was analyzed, a coefficient of determination of 0.75 was obtained (Fig. 9b), the MAD 35 g being when the median was 248 g.
- On testing the actual number of berries and the number of berries estimated by the point cloud, a determination value of 0.80 was obtained (Fig. 10a). The MAD of this fitting was 15 units, the median being 98 units. When this estimation was performed with CAD modelling, a coefficient of determination of 0.78 was obtained (Fig. 10b). In this case the MAD was 15 units when the median was 114 units.

From this analysis, it is possible to conclude that the semi-automatic process does not provide significant improvements, in contrast to the automatic one, which also has the advantage of a

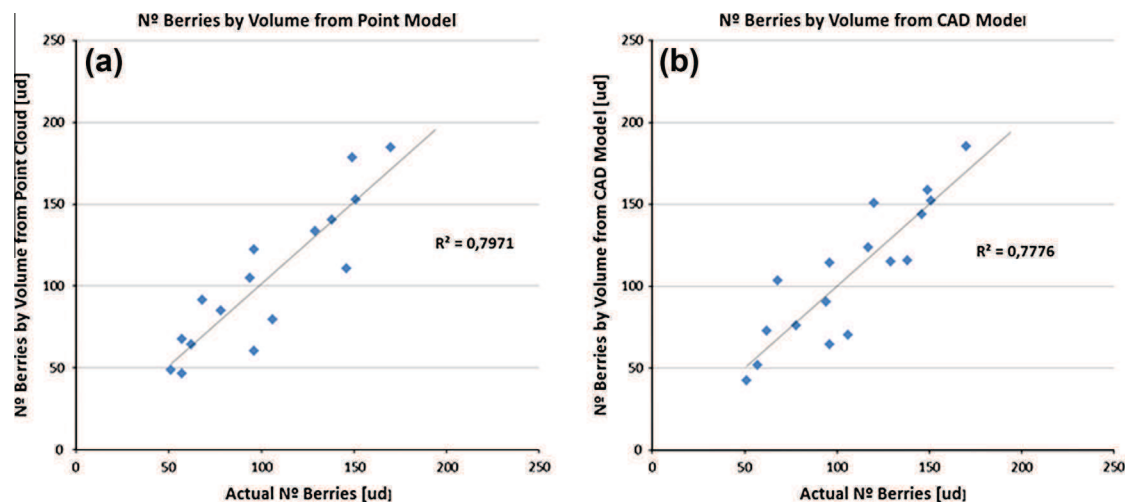


Fig. 10. Number of berries obtained automatically from point cloud (a) and number of berries obtained semi-automatically from CAD model (b).

reduced processing time and does not require human interaction. It significantly decreases subjective variability as well as featuring reduced associated costs and time saving. Furthermore, comparing the coefficients obtained with other yield estimation studies, this method can be cataloged as a great accurate one. Related to this assertion, [Diago et al. \(2012\)](#) achieved a R^2 of 0.73 between the observed and predicted yield values. [Dunn and Martin \(2004\)](#) succeeded a R^2 of 0.85 between grape weight and the ratio of grape pixels to total image pixel. Both cases used approaches based on supervised classification methodologies and an limited 2D analysis of bunch morphology. Additionally, both approaches required the employment of white screen to avoid the background influence which limits their effectiveness and automation in field.

5. Conclusions

This research presents a non-invasive low-cost method with application to precision viticulture that consists of vineyard yield estimation. The method is fast, reliable, robust and objective, and could serve to take decisions in advance regarding actions to be taken in vineyards, predicting the results and planning the vintage optimally. The method developed relies on the adaptation of the PW software tool, which allows the metric reconstruction and dimensional analysis of bunches from grapevine images taken in field conditions. The groundtruth established in laboratory tests ensures that the method is precise in complex agronomic scenarios and in trellis vine configurations, which are more complex to photograph than classic pruned configurations. The advantages of PW include process automation, sufficient quality to generate dense resolution models equivalent to the pixel size of the image, and low cost and ease of use.

Regarding the two processes developed to estimate vineyard production parameters (point cloud-automatic and CAD-semiautomatic), the results show that there is no significant improvement in CAD berry modelling. This is why the automatic methodology using integrated algorithms in PW software was selected for the present work. In addition, working only on one side of the cluster, the visible side, is feasible for approximating the whole bunch with an accurate and precise fit.

This methodology can be extrapolated to the whole of the vineyard, measuring its yield. Because this method is based on non-invasive technologies through a passive sensor, the constraints mainly depend on weather conditions, such as homogeneous lighting and the absence of rain and strong winds. By using artificial

light and simple screens to diffuse light, several restrictions can be overcome. Since future prospects will address cluster compactness and its relationship to volumes, another action to be developed in the future will be to design and build a platform that supports the configuration of the image acquisition protocol described in Section 2.1 and that can be loaded on a mobile platform such as a quad. This would also allow the optimal distances between sensors to be determined and calibrated and hence the possibility of scaling models without targets, significantly optimizing the time devoted to field work and data processing.

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References

- Aguilar, M.A., Pozo, J.L., Aguilar, F.J., Sanchez-Hermosilla, J., Páez, F.C., Negreiros, J., 2008. 3D surface modelling of tomato plants using close-range photogrammetry. *Int. Archives Photogr., Remote Sens. Spatial Informat. Sci.*, 330.
- Akca, D., Gruen, A., 2007. Generalized Least Squares Multiple 3D Surface Matching. *Institute of Geodesy and Photogrammetry, ETH Zurich*.
- Attene, M., 2010. A lightweight approach to repairing digitized polygon meshes. *Visual Comput.* 26 (11), 1393–1406.
- Barber, C.B., Dobkin, D.P., Huhdanpaa, H., 1996. The quickhull algorithm for convex hulls. *ACM Transact. Math. Software (TOMS)* 22 (4), 469–483.
- Barequet, G., Kumar, S., 1997. Repairing CAD models. In: *Visualization'97, Proceedings, IEEE*, pp. 363–370.
- Barequet, G., Sharir, M., 1995. Filling gaps in the boundary of a polyhedron. *Comput. Aided Geom. Des.* 12 (2), 207–229.
- Battany, M., 2008. A practical method for counting berries based on image analysis. In: *2nd Annual National Viticulture Research Conference, University of California, Davis, USA, 4–5, July 9–11*.
- Bay, H., Tuytelaars, T., Van Gool, L., 2006. Surf: speeded up robust features. In: *Computer Vision—ECCV 2006. Springer, Berlin Heidelberg*, pp. 404–417.
- Besl, P.J., Jain, R.C., 1988. Segmentation through variable-order surface fitting. *Pattern Anal. Machine Intell., IEEE Trans. on* 10 (2), 167–192.
- Blom, P.E., Tarara, J.M., 2009. Trellis tension monitoring improves yield estimation in vineyards. *HortScience* 44 (3), 678–685.
- Bøhn, J.H., Wozny, M.J., 1992. Automatic CAD-model repair: shell-closure. In: *Proc. Symp. on Solid Freeform Fabrication*, pp. 86–94.
- Branch, D., Dang, L.C., Hall, N., Ketchum, W., Melakayil, M., Parrent, J., Baron, E., 2006. Comparative direct analysis of type Ia supernova spectra. II. Maximum light. *Publ. Astron. Soc. Pac.* 118 (842), 560–571.

- Chherawala, Y., Lepage, R., Doyon, G., 2006. In food grading/sorting based on color appearance through machine vision: the case of fresh cranberries. *Informat. Commun. Technol.*, 1540–1545, ICTTA '06, 2nd, 0–0 0.
- Clingeffer, P.R., Martin, S., Krstic, M., Dunn, G.M., 2001. Crop development, crop estimation and crop control to secure quality and production of major wine grape varieties: a national approach: final report to grape and wine research development corporation. Grape and Wine Research & Development Corporation.
- DeLuca, J.G., Gall, W.E., Ciferri, C., Cimini, D., Musacchio, A., Salmon, E., 2006. Kinetochore microtubule dynamics and attachment stability are regulated by Hec1. *Cell* 127 (5), 969–982.
- Deseilligny, M.P., Clery, I., 2011. Apero, an open source bundle adjustment software for automatic calibration and orientation of set of images. In: *Proceedings of the ISPRS Symposium, 3DARCH11*, pp. 269–277.
- Desolneux, A., Moisan, L., Morel, J.M., 2000. Meaningful alignments. *Int. J. Comput. Vision* 40 (1), 7–23.
- Diago, M.-P., Correa, C., Millán, B., Barreiro, P., Valero, C., Tardaguila, J., 2012. Grapevine yield and leaf area estimation using supervised classification methodology on RGB images taken under field conditions. *Sensors* 12, 16988–17006.
- Djuricic, A., Weinmann, M., Jutzi, B., 2014. Potentials of small, lightweight and low cost multi-echo laser scanners for detecting grape berries. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XL-5, 2014. In: *ISPRS Technical Commission V Symposium*, 23–25 June 2014, Riva del Garda, Italy.
- Dolenc, A., Makela, I., 1993. Some efficient procedures for correcting triangulated models. In: *Proceedings of Solid Freeform Fabrication Symposium*, pp. 126–134.
- Dunn, G.M., Martin, S.R., 2003. The current status of crop forecasting in the Australian wine industry. *ASVO Seminar Series: Grapegrowing at the Edge*, 24.
- Dunn, G.M., Martin, S.R., 2004. Yield prediction from digital image analysis: a technique with potential for vineyard assessments prior to harvest. *Aust. J. Grape Wine Res.* 10 (3), 196–198.
- Fan, Y.Z., Tam, B.S., Zhou, J., 2008. Maximizing spectral radius of unoriented Laplacian matrix over bicyclic graphs of a given order. *Linear and Multilinear Algebra* 56 (4), 381–397.
- Fischler, M.A., Bolles, R.C., 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Commun. ACM* 24 (6), 381–395.
- Golias, N.A., Dutton, R.W., 1997. Delaunay triangulation and 3D adaptive mesh generation. *Finite elements Anal. Des.* 25 (3), 331–341.
- Gonzalez-Aguilera, D., Del Pozo, S., Lopez, G., Rodriguez-Gonzalez, P., 2012. From point cloud to CAD models: Laser and optics geotechnology for the design of electrical substations. *Opt. Laser Technol.* 44 (5), 1384–1392.
- González-Aguilera, D., Guerrero, D., Hernández-López, D., Rodríguez-González, P., Pierrot, M., Fernández-Hernández, J., 2013. PW, Photogrammetry Workbench. <<http://www.isprs.org/catcon/catcon6.aspx>> (accessed 30.04.14).
- Greven, M., 2007. Manual for yield forecasting in Sauvignon Blanc grapes. Marlborough Wine Research Centre.
- Gruen, A., 1985. Adaptive least squares correlation: a powerful image matching technique. *South African J. Photogr., Remote Sens. Cartogr.* 14 (3), 175–187.
- Guskov, I., Wood, Z.J., 2001. Topological noise removal. In: *2001 Graphics Interface Proceedings*. Ottawa, Canada, 19.
- Hartley, R., Zisserman, A., 2003. *Multiple View Geometry in Computer Vision*. Cambridge University Press.
- Herrero Langreo, A., Barreiro Elorza, P., Santamaria, D., Paz, M., Baluja, J., Ochagavia, H., 2010. Pixel classification through mahalanobis distance for identification of grapevine canopy elements on rgb images.
- Hirschmuller, H., 2005. Accurate and efficient stereo processing by semi-global matching and mutual information. In: *Computer Vision and Pattern Recognition*. CVPR 2005. In: *IEEE Computer Society Conference on*, vol. 2, pp. 807–814.
- Joglekar, J., Gedam, S.S., 2012. Area based image matching methods—a survey. *Int. J. Emerg. Technol. Adv. Eng.* 2, 130–136.
- Kraus, K., 1993. *Photogr. Fundamentals Standard Processes*, vol. 1. DummlersVerlag, Bonn, Germany, ISBN 3-427-78684-6.
- Kurtural, K., ÓDaniel, B., 2007. Crop estimation in vineyards. *UK Cooperat. Extens. Service Univ. Kentucky-College Agric.*, 45.
- Lange, B., Chang, C., Suma, E., Newman, B., Rizzo, A.S., Bolas, M., 2011. Development and evaluation of low cost game-based balance rehabilitation tool using the microsoftkinect sensor. *Engineering in Medicine and Biology Society, EMBC, In: 2011 Annual International Conference of the IEEE*, pp. 1831–1834.
- Longuet-Higgins, H.C., 1987. A computer algorithm for reconstructing a scene from two projections. In: *Fischler, M.A., Firschein, O. (Eds.), Readings in Computer Vision: Issues, Problems, Principles, and Paradigms*, pp. 61–62.
- Lowe, D., 1999. Object recognition from local scale-invariant features. In: *International Conference on Computer Vision*, Corfu, Greece.
- Lowe, D.G., 2004. Distinctive image features from scale-invariant keypoints. *Int. J. Comput. Vision* 60 (2), 91–110.
- Lumme, J., Karjalainen, M., Kaartinen, H., Kukko, A., Hyypää, J., Hyypää, H., et al., 2008. Terrestrial laser scanning of agricultural crops. *Int. Archives Photogr., Remote Sens. Spatial Informat. Sci.* 37, 563–566.
- Martin, S., Dunstone, R., Dunn, G., 2003. How to Forecast Wine Grape Deliveries Using Grape Forecaster Excel Workbook Version 7. GWRDC, Adelaide, Australia, p. 100.
- Matas, J., Chum, O., Urban, M., Pajdla, T., 2004. Robust wide-baseline stereo from maximally stable extremal regions. *Image Vis. Comput.* 22 (10), 761–767.
- Moisan, L., Stival, B., 2004. A probabilistic criterion to detect rigid point matches between two images and estimate the fundamental matrix. *Int. J. Comput. Vision* 57 (3), 201–218.
- Moisan, L., Moulon, P., Monasse, P., 2012. Automatic homographic registration of a pair of images, with a contrario elimination of outliers. *Image Processing On Line*, 10.
- Morel, J.M., Yu, G., 2009. ASIFT: a new framework for fully affine invariant image comparison. *SIAM J. Imag. Sci.* 2 (2), 438–469.
- Mosteller, F., Tukey, J., 1977. *Data Analysis and Regression*. Addison-Wesley, Upper Saddle River, NJ.
- Nuske, S., Achar, S., Bates, T., Narasimhan, S., Singh, S., 2011. Yield estimation in vineyards by visual grape detection. *Intelligent Robots and Systems (IROS)*. In: *2011 IEEE/RSJ International Conference on*, pp. 2352–2358.
- Nuske, S., Gupta, K., Narasimhan, S., Singh, S., 2012. Modeling and Calibrating Visual Yield Estimates in Vineyards. In: *Yoshida, K., Tadokoro, S. (Eds.), Field and Service Robotics*, vol. 92. Springer, Berlin Heidelberg, pp. 343–356.
- O'Rourke, J., 1994. *Computational Geometry*. C. Press Syndicate of the University of Cambridge, p. 118.
- Pope, A.J., 1976. The statistics of residuals and the detection of outliers.
- Quan, L., 2010. *Image-Based Modeling*. Springer, New York.
- Roby, G., Harbertson, J.F., Adams, D.A., Matthews, M.A., 2004. Berry size and vine water deficits as factors in winegrape composition: anthocyanins and tannins. *Aust. J. Grape Wine Res.* 10 (2), 100–107.
- Rock, S.J., Wozny, M.J., 1992. Generating topological information from a bucket of facets. In: *Solid Freeform Fabrication Symposium Proceedings*. The University of Texas at Austin, Austin, pp. 251–259.
- Romero, I., García-Escudero, E., Martín, I., 2010. Effects of leaf position on blade and petiole mineral nutrient concentration of Tempranillo grapevine (*Vitis vinifera* L.). *Am. J. Enol. Viticulture* 61 (4), 544–550.
- Sachs, L., 1984. *Applied Statistics: A Handbook of Techniques*. Springer-Verlag, New York, p. 253.
- Serrano, L., González-Flor, C., Gorchs, G., 2012. Assessment of grape yield and composition using the reflectance based water index in Mediterranean rainfed vineyards. *Remote Sens. Environ.* 118, 249–258.
- Sethian, J.A., 1999. *Level Set Methods and Fast Marching Methods: Evolving Interfaces in Computational Geometry, Fluid Mechanics, Computer Vision, and Materials Science*, vol. 3. Cambridge University Press.
- Smith, S.M., Brady, J.M., 1997. SUSAN—a new approach to low level image processing. *Int. J. Comput. Vision* 23 (1), 45–78.
- Varnuška, M., Parus, J., Kolingerová, I., 2005. Simple holes triangulation in surface reconstruction. In: *Proceedings of ALGORITHM*, pp. 280–289.
- Vicente Renedo, T., Martínez García, J., Chavarri, J.B., Marín, M., González Marciano, S., Domínguez Miguel, N., Villar Capellán, R., 2007. Preservation of genetic heritage of authorized vinifera grapes and rootstocks in Rioja DOC [Designation of Origin]. In: *Foro Mundial del Vino*, 5, Logroño (España), 28–30 Mar 2006. GLR, CAGDR.
- Wang, J., Gu, D., Yu, Z., Tan, C., Zhou, L., 2012. A framework for 3D model reconstruction in reverse engineering. *Comput. Ind. Eng.* 63 (4), 1189–1200.
- Whalley, J., Shanmuganathan, S., 2013. In Applications of image processing in viticulture: A review. In: *20th International Congress on Modelling and Simulation*, Adelaide, Australia, pp. 531–537.
- Wolpert, J., Vilas, E., 1992. Estimating vineyard yields: introduction to a simple, two-step method. *Am. J. Enol. Viticul.* 43 (4), 384–388.

3.3. Modelos Digitales Densos de Altura de Cubierta Vegetal por medio de una plataforma fotogramétrica de bajo coste y datos LiDAR

Este estudio propone una metodología de bajo coste, eficiente y precisa para la obtención de Modelos Digitales de Altura de Cubierta Vegetal (CHM) destinados a la gestión forestal. Se consigue mediante la integración de datos terreno de escasa variabilidad temporal procedentes del LiDAR y de libre difusión por parte del Instituto Geográfico Nacional (IGN) en las nubes de puntos fotogramétricas obtenidas con una plataforma low-cost y en el área y momento de interés. De esta manera, se combinan la capacidad de detección del terreno en zonas de vegetación densa, procedente de la tecnología LiDAR con la mayor resolución espacial, radiométrica y temporal que ofrece la fotogrametría low-cost en la zona de la cubierta vegetal. Como plataforma fotogramétrica de bajo coste se propone un powered paraglider trike, que embarca un sistema multisensorial específico, MUSAS (MULTiSpectral Airborne System), diseñado y desarrollado por parte del Instituto de Desarrollo Regional de la Universidad de Castilla-La Mancha (IDR). La mayor ventaja que ofrece este tipo de plataformas tripuladas es su flexibilidad de vuelo y autonomía, lo que permite la adquisición de datos de una superficie extensa en un instante determinado.

El ámbito de actuación se situó en una zona de monte público del término municipal de Bienservida, provincia de Albacete (España) con una superficie de estudio de 2.01 km². Ésta resulta de mucho interés desde el punto de vista forestal debido a que se trata de una zona de masa forestal de pinus nigra con distintas fracciones de cabida cubierta según el IFN (Inventario Forestal, España), siendo un área de alta densidad forestal y de relieve accidentado, lo que dificulta la aplicación de métodos clásicos forestales. Se estableció una campaña de apoyo topográfico para obtener la georreferenciación absoluta y escalado del modelo fotogramétrico, mediante la medición de tarjetas artificiales de puntería repartidas por la zona de estudio.

La obtención de la nube de puntos fotogramétrica se realizó mediante el software *Photogrammetry Workbench* (PW) desarrollado por los autores (González-Aguilera et al., 2013), en el que los puntos de interés se detectan a través del algoritmo SIFT (Lowe, 2004) y los parámetros externos de la cámara (posición y orientación) y los parámetros internos se resuelven por auto-calibración. Finalmente se obtiene la nube de puntos de

color por medio de la intersección de rayos (Kraus, 2007), resolviendo este proceso a partir de una técnica de SGM (Semi-Global Matching) (Pierrot-Deseilligny y Clery, 2011).

Una vez obtenida la nube de puntos fotogramétrica, se clasificó la vegetación a través de un proceso supervisado basado en el color de las imágenes, que permite mejorar los métodos de clasificación de tipo morfológico (Wang et al., 2007). En esta fase se empleó la herramienta "Vegetation Classification by Radiometry" del programa *Metric Computations On Forestry Point Clouds* desarrollado por el Dr. David Hernández López de la Universidad de Castilla-La Mancha. El proceso se fundamenta en un análisis de las diferencias porcentuales de los niveles digitales entre pares de canal (BG y RB). Los puntos son clasificados automáticamente de acuerdo a un umbral definido por un valor verde de referencia. Debido a que los tonos verdes dependen de muchos factores, como los sensores empleados, las condiciones y la fecha de vuelo, tipo de especies y estado fenológico de la vegetación... es necesario establecer el valor umbral de la vegetación según el modelo fotogramétrico.

La fotogrametría low-cost conlleva errores de georreferenciación producidos por el empleo de sensores inerciales y GNSS de baja precisión y cámaras no métricas. Es por ello que se diseñó un *modelo de correcciones* para integrar datos LiDAR del terreno en la nube fotogramétrica depurada, alcanzando una precisión en la fusión compatible estadísticamente con las precisiones de ambas técnicas en base a los principios de la fotogrametría clásica y el procesamiento LiDAR (0.47m). Se trata de un modelo derivado de las diferencias altimétricas del terreno entre ambos dataset. Para rechazar los outliers del cálculo del modelo de correcciones, se eliminaron los puntos cuya diferencia altimétrica no pertenecía al intervalo de confianza relativo a la probabilidad del 95% (St-Onge et al., 2008).

Una vez fundidos ambos dataset, se obtuvieron los distintos modelos digitales relativos al terreno (DTM), superficie (DSM) y la cubierta vegetal (CHM) mediante la generación de mallas triangulares de la nube clasificada fusionada, eliminando los errores groseros generados gracias a la aproximación de Attene (2010). Finalmente, el CHM se obtuvo a partir de la diferencia entre el DSM procedente de la fotogrametría y el DTM resultante de la fusión de las nubes de puntos (Jarnstedt et al., 2012), representando las alturas

normalizadas de la vegetación respecto a la superficie del terreno, con una resolución planimétrica de 1 m (D'Oliveira et al., 2012).

Los resultados obtenidos permitieron examinar la evolución del crecimiento forestal. Por ello, se analizó la distribución de la diferencia de volumen vegetal entre el CHM procedente de datos LiDAR tomados en el año 2009 y el generado a partir de la nube hibridada a finales del 2013, ambos con referencia a su respectivo MDT. El aumento de biomasa sufrido en esos años es debido a la legislación proteccionista llevada a cabo durante los últimos años en esa zona (Cerro and Lucas, 2007).

La metodología propuesta reduce los tiempos de adquisición, de procesado y, en definitiva, los costes económicos frente a las técnicas tradicionales de inventario forestal, con la ventaja añadida de obtener información vectorial en forma de nubes de puntos clasificadas de la zona. Esto implica un incremento de la precisión final a nivel de rodal y facilidad en la integración y gestión de la información forestal en Sistemas de Información Geográficos. Al mismo tiempo desaparece la subjetividad asociada a la incertidumbre que genera el operador.

Palabras clave: *modelo digital de altura de cubierta vegetal, fotogrametría, LiDAR, fusión de datos, plataforma de bajo coste, segmentación radiométrica.*

Dense Canopy Height Model from a low-cost photogrammetric platform and LiDAR data

Mónica Herrero-Huerta¹ · Beatriz Felipe-García² · Soledad Belmar-Lizarán³ ·
David Hernández-López³ · Pablo Rodríguez-Gonzálvez¹ · Diego González-Aguilera¹

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Abstract

Key message Low-cost methodology to obtain CHMs integrating terrain data from LiDAR into photogrammetric point clouds with greater spatial, radiometric and temporal resolution due to a correction model.

Abstract This study focuses on developing a methodology to generate a Dense Canopy Height Model based on the registration of point clouds from LiDAR open data and the photogrammetric output from a low-cost flight. To minimise georeferencing errors from dataset registration, terrain data from LiDAR were refined to be included in the photogrammetric point cloud through a correction model supported by a statistical analysis of heights. As a result, a fusion point cloud was obtained, which applies LiDAR to characterize the terrain in areas with high vegetation and utilizes the greater spatial, radiometric and temporal resolution of photogrammetry. The obtained results have been successfully validated: the accuracy of the fusion cloud is statistically consistent with the accuracies of both clouds based on the principles of classical photogrammetry and LiDAR processing. The resulting point cloud, through a

radiometric and geometric segmentation process, allows a Dense Canopy Height Model to be obtained.

Keywords Dense Canopy Height Model · Photogrammetry · LiDAR · Data fusion · Low-cost platform · Radiometric segmentation

Introduction

The estimation of dasometric variables of interest for forest management (diameter, height, basal area, volume of growing stock, biomass, species, etc.) has traditionally been done via pilot samplings of field inventories. The advent of new remote sensing technologies and photogrammetry has opened up a new field of possibilities for carrying out such work, and such methods are advantageous in the economic costs involved, the time invested and estimation errors.

The application of active high-resolution remote sensors affords high accuracy in height measurements and a good prediction of dasometric variables (Popescu et al. 2002). In particular, the capacity of active light detection and ranging (LiDAR) sensors to penetrate and acquire three-dimensional measurements of the canopy at different heights (Wulder et al. 2013) allows improved estimation of variables such as biomass, volume and basal area over that of other sensors that gather two-dimensional data, such as photographic or radiometric systems. Since the late 1980s, studies have been published based on profiles acquired using airborne laser systems (ALS—airborne laser scanner) for the estimation of biomass and volumes (Nelson et al. 1988) as well as simple and multiple linear models (Nelson et al. 1997; Means et al. 2000) to analyse the effect of the lag transformation of the forest variable. Later studies

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✉ Mónica Herrero-Huerta
monicaherrero@usal.es

¹ Department of Cartographic and Land Engineering, Higher Polytechnic School of Avila, University of Salamanca, Hornos Caleros 50, 05003 Ávila, Spain

² Forestry and Natural Spaces Service, Agriculture, Environment and Rural Development Department, Castilla-La Mancha Regional Government, C/Mayor 46, 02001 Albacete, Spain

³ Institute for Regional Development (IDR), University of Castilla La Mancha, 02071 Albacete, Spain

(Naesset 1997; Nelson et al. 2003) have improved upon studies of forest inventories by further exploiting instrumentation, capture methodology and information processing. Of interest are the studies of Lim and Treitz (2004) and Naesset (2004), in which the authors applied rodal¹ methods to generate inventories, as well as individual tree methods,² in which methodological compendia are described with the algorithms used in each estimation. Comparisons of different LiDAR inventories (Naesset et al. 2005) and of photointerpretation and LiDAR (Eid et al. 2004) have been published.

In recent years, many studies and methodological review articles have been published describing the operating capacity and definitive implementation of LiDAR technology in the context of the extraction of forest variables (Hyypä et al. 2008; Wulder et al. 2012; Kankare et al. 2013). Benko and Balenovic (2011) reported new experiences in inventory tasks and forest management in different environments, with an analysis of the accuracies achieved. Richardson and Moskal (2011) established classifications of vegetation via tree height and density. Another interesting case is the guide produced by the Canadian Forest Service as a current reference document based on all previously published studies. The guide provides a series of recommendations for inventorying forest applications based on rodal methods using LiDAR data (White et al. 2013a). Gleason and Im (2012) applied different automated learning approaches to estimate biomass in forests from aerial LiDAR data. The FullWave airborne LiDAR systems provide large bodies of information about the overall plant and forest structure in great detail (Weinacker et al. 2004; Mallet and Bretar 2009). However, the complex and tedious processing involved and the costs of such technology are definite drawbacks (Chauve et al. 2007; Gupta et al. 2010).

Magnussen et al. (2007) used Landsat satellite images to create inventories according to the spatial resolution factor. Similarly, LiDAR techniques have been applied to images captured by different remote sensing systems (Magnussen et al. 2000; Wulder et al. 2008a, b; Willers et al. 2012; Mora et al. 2013) and by traditional photogrammetry (Magnusson et al. 2007).

Within the framework of the National Aerial Orthoimage Plan, low-density (0.5 points/m²) LiDAR sensor flights have been performed since 2008 throughout the Spanish territory. Thus, in recent years, different forest research teams have tested different applications using data from this source (Estornell et al. 2012; González-Ferreiro et al.

2014; Gonzalez et al. 2012; Navarro-Cerrillo et al. 2014). The problem with these mass data acquisitions is that they are very costly, their resolution is low, and they are implemented individually at a given moment in time.

Currently, conventional photogrammetry is a complementary alternative to custom LiDAR flights to obtain 3D-point clouds and digital surface models (DSMs) because the associated costs are lower (Järnstedt et al. 2012); the accuracy is greater; and the spatial, radiometric and temporal resolution is greater (Bohlin et al. 2012). The complementary nature of the two techniques can be seen in the greater planimetric accuracy of photogrammetry than LiDAR and the greater altimetric accuracy of the latter than of the former. Nevertheless, photogrammetry is incapable of generating a Digital Terrain Model (DTM) in zones covered by vegetation, and LiDAR information must be used to generate reference surfaces for the collection of vegetation heights (Järnstedt et al. 2012). As an advantage of the photogrammetric point cloud, White et al. (2013b) cite the ability to interpret species composition as well as the maturity and health of vegetation.

With the development of manned and unmanned low-cost aerial platforms (RPAS—Remotely Piloted Aircraft Systems), conventional photogrammetric data collection and analysis can still be performed. Tao et al. (2011) used dense photogrammetric point clouds obtained with RPAS over forested areas and obtained information about the tree density, its composition and changes in the forest canopy. Other authors (Jaakkola et al. 2010; Wallace et al. 2012) have combined cameras and light LiDAR systems on RPAS, thus allowing both sensors to be used at the same time. Finally, special attention should be paid to the study of Lisein et al. (2013), in which the authors generated a Canopy Height Model (CHM) of a hybrid nature, combining the DSM obtained by correlating images from a non-metric camera and an RPAS with a DTM obtained from ALS data to estimate different forest parameters.

The aim of the present work was to develop a low-cost, efficient and precise methodology to obtain CHMs destined for forest inventories such a stratification of forest masses or a stock calculation and for fire studies obtaining combustible models. This was achieved by integrating LiDAR terrain data with minor temporal variability, which are freely available from the National Geographic Institute of Spain, into photogrammetric point clouds obtained using a low-cost platform, for a desired area and time. Thus, we combined LiDAR's terrain-sensing capacity in densely vegetated zones with the greater spatial, radiometric and temporal resolution offered by low-cost photogrammetry in plant cover zones. A correction model was constructed for the two data sources to minimise the georeferencing errors produced by the low-cost photogrammetric process, thereby obtaining a registration accuracy in agreement with the accuracies of

¹ Rodal method: methods applied to a surface with similar arboreal characteristics.

² Individual-tree methods: methods applied differentially to each tree.

the point clouds generated by the two techniques. During data analysis, following the recommendations of Wang et al. (2007), we also incorporated a supervised classification of the vegetation based on image colour that allows morphological classification types to be improved. The low-cost photogrammetric platform we used was a powered paraglider trike, designed and developed by the Institute for Regional Development of the University of Castilla-La Mancha. The greatest advantage offered by this type of manned platform is its flexibility of flight, autonomy and payload capacity, allowing data acquisition over an extensive area using multiple sensors to be integrated without constraints on time, weight or volume.

Materials and methods

The proposed methodology uses LiDAR open data freely available from the National Geographic Institute of Spain (IGN 2015) with a spatial resolution of 0.5 points/m². The aerial LiDAR data were revised by visual inspection and later by manual refinement, correcting errors in the initial automatic classification and thus obtaining well-coded terrain points. To assess the quality of the classification, the initial and filtered data were contrasted by means of a confusion matrix (Kohavi and Provost 1998).

According to the technical specifications of the National Aerial Orthoimage Plan (CNIG 2009), based on the type of terrain and the vegetation, an altimetric accuracy of 0.40 m was established.

Equipment

The following equipment was employed for photogrammetric data acquisition:

- A Leica System 1200 GNSS-RTK device was used for surveying control and check points, with a relative and absolute precision better than 0.03 and 0.05 m, respectively.
- A compact Olympus EP-1 camera, the first camera which meets the design standards of the micro four

thirds (MFT) system. Its main features are shown in Table 1.

- A manned aerial platform supported by a powered paraglider (PPG) trike built by Airges (Fig. 1) was used (Ortega-Terol et al. 2014). Its technical specifications are shown in Table 2. The Olympus EP-1 camera was installed aboard the PPG trike using an auto-stabilised mounting platform. The potential benefits of this low-cost system are evident: a payload capacity that allows the system to be loaded with a large number of sensors that could be used for multispectral studies; the



Fig. 1 Aerial photogrammetric platform (PPG trike) with the gimbal shown (white rectangle)

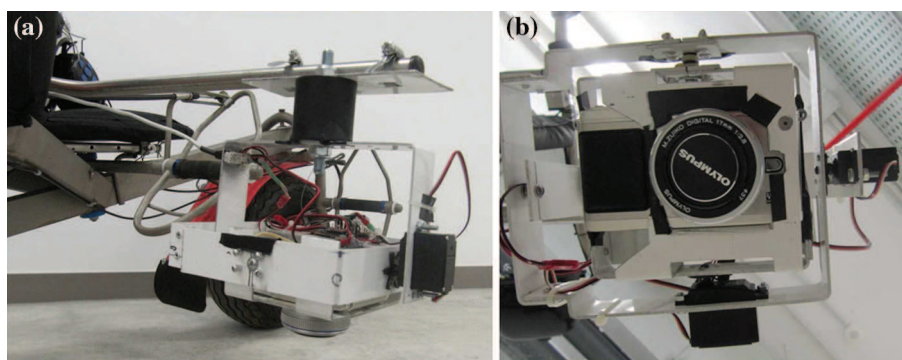
Table 2 Technical specifications of the manned aerial platform: PPG trike

Parameter	Value
Empty weight	110 kg
Maximum load	220 kg
Autonomy	3.5 h
Maximum speed	60 km/h
Motor	Rotax 503
Tandem paraglide	MACPARA Pasha 4
Emergency system	Ballistic Parachutes GRS 350
Gimbal	Stabilized with 2 degrees of freedom
Minimum sink rate	1.1
Maximum glide	8.6
Plant surface	42.23 m ²
Projected area	37.8 m ²
Wingspan	15.03 m
Plant elongation	5.35
Central string	3.51 m
Boxes	54
Zoom factor	100 %

Table 1 Technical specifications of the photographic sensor

Olympus EP1	
Type	CMOS
Sensor size (max. resolution)	4032 × 3024 pixels
Sensor size	17.3 × 13 mm
Pixel size (sensor geometric resolution)	0.0043 mm
Focal length	17 mm
Total pixels	12.3 MPixel
Aperture	f/2.8

Fig. 2 Gimbal platform (auto-stabilised mounting platform). **a** Elevation view and **b** plan view



flexibility and autonomy of flying that offers the data acquisition over extensive areas.

- The PPG was equipped with a low-cost multi-sensor gimbal (stabilised platform), supporting the digital camera. The gimbal includes two servomotors oriented on the x and y axes to accurately maintain the camera's vertical position along the flight paths. The servomotors are controlled by an Arduino board, which incorporates an IMU with 6 degrees of freedom: three accelerometers with a range of $\pm 3.6 \text{ G m/s}^2$, a double-shaft gyroscope (for pitch and roll) and an additional gyroscope for yaw (both gyroscopes have a measurement range of $\pm 300^\circ/\text{s}$). The software developed to control the device is based on Quadl_mini V 20 software, with DCM (Direction Cosine Matrix) as the IMU management algorithm (Premarlani and Bizard 2014). Figure 2 shows the gimbal platform.
- The system included a low-cost GNSS system based on a single-frequency receptor, receiving signals from a GPS constellation and Satellite Based Augmentation System (SBAS) (NavCen 2008). The GNSS antenna is installed on the camera platform close to the optical centre of the camera to minimise the baseline. To improve the GNSS altitudinal accuracy, which affects the final GSD, a DigiFly VL100 barometer was installed. Thus, horizontal positioning during flight was performed using the GNSS system's National Marine Electronics Association (NMEA) protocol using RTKNAVI software (Takasu 2009), with corrections from the ground from similar equipment, allowing DGPS accuracies higher than 1.50 m in planimetry and 2 m in altimetry to be achieved in real time as well as accuracies higher than 0.50 m in three dimensions in post-processing.

Flight planning and execution

Proper flight planning is important to ensure that the captured photogrammetric data will fit the desired theoretical

parameters; planning also optimises available resources and ensures higher quality images, minimising capture time. Flight planning was conducted with software developed by the IDR (Institute of Regional Development of Castilla-La Mancha, Spain), called PFlip, utilising fundamentals of photogrammetry, the sensor configuration, and the Digital Terrain Model (Hernández-López et al. 2013).

First, the study area was defined, followed by the flight strips. Furthermore, additional constraints such as a minimum forward overlap of 70 % and a minimum side overlap of 30 % were established to ensure automatic detection of tie points (Järnstedt et al. 2012). Then, the flight planning process defined the position and orientation of the camera, the design of different blocks of images, the overlaps between different images, the necessary shot angles and the scale, as defined by the choice of pixel size on the ground (GSD).

The geomatic information required for the flight planning process was obtained at no cost from the National Center of Geographic Information in Spain (CNIG 2015), from its National Aerial Orthoimage Plan, with a GSD of 0.25 m and a Digital Terrain Model with a 5-m grid resolution.

Flight planning was performed by considering the relationship among the flight height over the ground (H), the GSD, the focal length of the sensor (f) and the pixel size, as described in Eq. (1).

$$\frac{f}{H} = \frac{\text{pixel size}}{\text{GSD}} \quad (1)$$

Considering Eq. (1), the characteristics of the camera (Table 1) and the required GSD of 0.08 m, a flight height over the ground of 316 m was obtained. Based on the technical specifications of the National Aerial Orthoimage Plan (CNIG 2009), an 'a priori' altimetric accuracy of 0.10 m was estimated for the photogrammetric cloud.

The parameters that define image capture are determined during flight execution depending on the light conditions, the camera quality and flight speed. Thus, the camera configuration was established with a camera-

shooting interval of 4 s and a maximum flight speed of 14 m/s, which guaranteed a forward overlap of 70 %. A shutter speed of 1/1000 s was adequate for this speed because the equivalent terrain displacement would be 0.01 m, which was lower than 1/5 pixel, an insignificant value for study purposes. An ISO of 125 was used with a fixed focal length at infinity.

A topographic survey campaign was established to obtain absolute georeferencing and a model scaled through artificial accuracy targets. Targets were distributed along the study area so that they remained visible through vegetation for photogrammetric capture. Moreover, these targets were marked and their size confirmed to rule out effects from neighbouring pixels (35 cm diameter).

Photogrammetric processing

Low-cost photogrammetric workflow

Once the aerial imagery had been acquired, conventional photogrammetric processing began, relying on an image-based modelling technique. In an attempt to guarantee automation and quality, a combination of photogrammetric and computer vision algorithms was required. This approach allows data to be acquired remotely with great efficiency and accuracy, affording radiometric characteristics to the point cloud. Photogrammetry Workbench software (PW) developed by the authors (González-Aguilera et al. 2013) was used for three steps. First, the images were matched by the SIFT algorithm (Lowe 2004), which allowed the detection of the scene's points of interest. Second, the camera orientations were computed using the tie-points calculated in the previous step and the coordinates of the artificial ground targets located in the flight area (Pierrot-Deseilligny and Clery 2011). In this process, the external camera parameters (position and orientation) and the internal camera parameters were solved by self-calibration. Finally, a textured point cloud was obtained by means of ray intersection (Kraus 2007). To solve this process, an semi-global matching (SGM) technique (Pierrot-Deseilligny and Clery 2011) was applied.

Photogrammetric point cloud processing

Owing to the massive and automated nature of the photogrammetric point cloud, it was necessary to treat the cloud to remove outliers and encode the information. More precisely, a clean-up and classification process was used; this approach is schematised in Fig. 3. After removing the outliers produced by matching, the vegetation was distinguished via radiometric segmentation. Following this step, we established geometric classification of the “non-vegetation” class to differentiate it from “ground”, refining the

results via a second iteration. Once the uncertain points in the “ground” class and the isolated terrain points had been removed, we classified the other points into different semantic categories using the Axelsson algorithm (1999): “ground”, “low vegetation”, “medium vegetation”, “high vegetation”, “building” and “noise”, according to the American Society for Photogrammetry and Remote Sensing (ASPRS Foundation 2012). During this process, special emphasis was placed on the classification of the “ground” class so that it would act as a common reference point for later collection of LiDAR and photogrammetric data. Additionally, it is crucial to achieve a correct DTM to obtain an accurate CHM.

Radiometric classification takes advantage of the RGB values of the photogrammetric point cloud. This step was carried out using in-house “Vegetation classification by radiometry” software. The analysis is based on the percentage differences between the digital levels of two channel pairs (R-G and R-B). Points were classified automatically according to a threshold defined by the difference from a green reference value. However, the values of green hues depend on many factors, such as the sensor employed, the conditions and date of flight, the type of species, the phenological state of the vegetation, etc. Accordingly, it is necessary to establish a threshold value from vegetation samples in the photogrammetric model.

Once the LiDAR information was corrected and the photogrammetric point cloud had been classified and refined, the point clouds were fused as described in the following section.

Fusion of point clouds

Before registering the point clouds, the ground photogrammetric points were filtered by cross-analysis with the LiDAR data to address errors caused in the classification process. To do so, we obtained a map of altimetric differences in ground-class zones shared between the two clouds. The photogrammetric points with large differences in height were reclassified as vegetation. We then generated a mask of the ground-class photogrammetric points to remove clusters of isolated points ($S < 2 \text{ m}^2$) and the points contained within polygons with a high mean altimetric difference ($h > 1 \text{ m}$). This filtering process allowed us to refine the terrain's photogrammetric data. Figure 4 shows the process used.

Low-cost photogrammetry includes georeferencing errors produced by the use of inertial sensors and low-accuracy GNSS and non-metric cameras. Accordingly, we designed a *correction model* to integrate the collected LiDAR data into the refined photogrammetric cloud, achieving a registration accuracy that was statistically compatible with the accuracy of both techniques. To

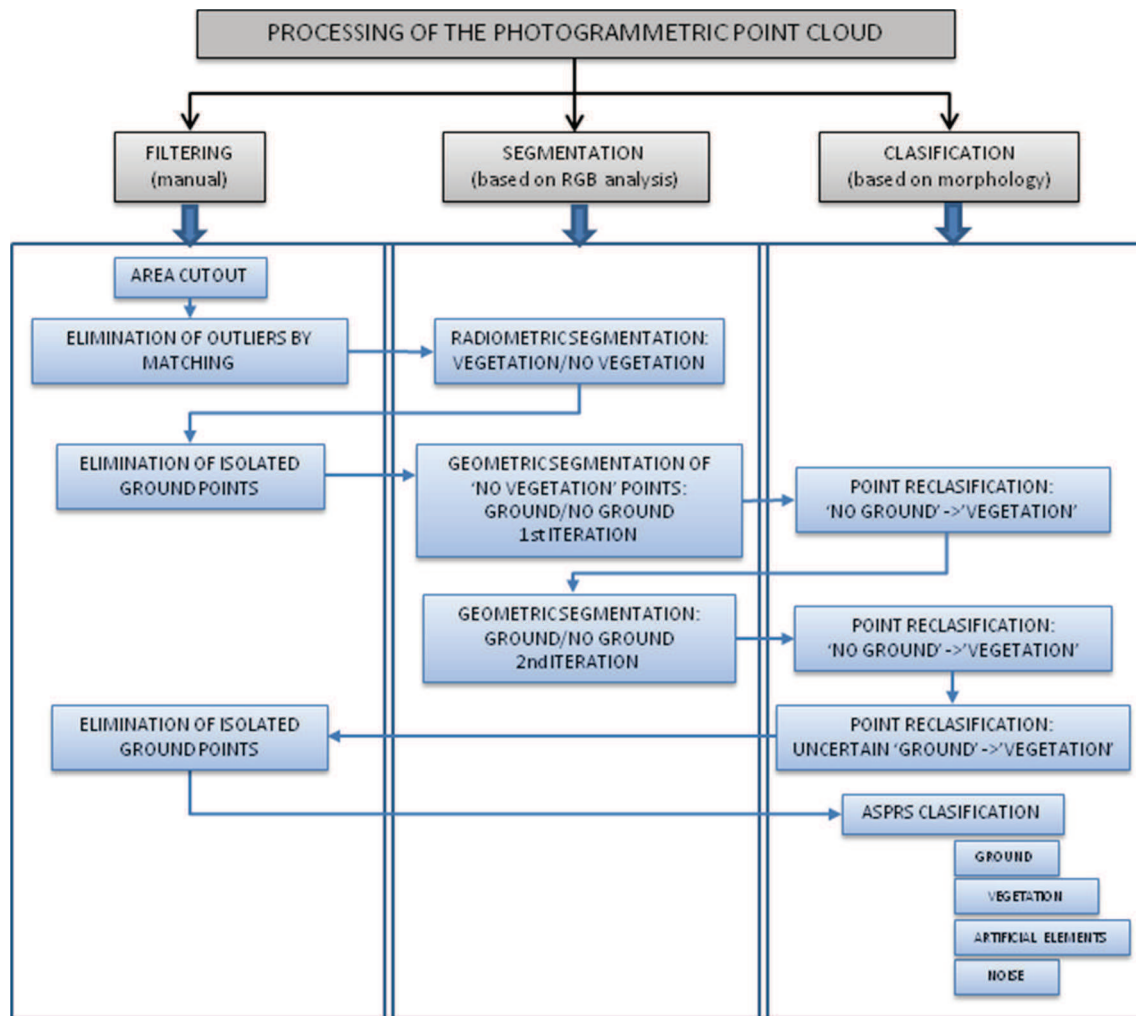


Fig. 3 Workflow for the processing and classification of the photogrammetric point cloud

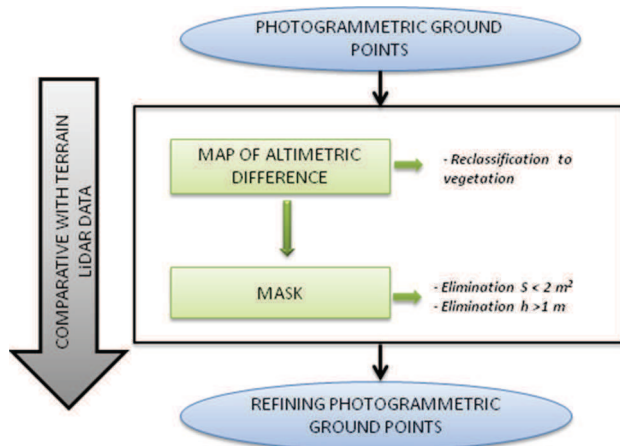


Fig. 4 Refining of the photogrammetric ground points through LiDAR data

analyse this compatibility, the ‘a priori’ (σ) and ‘a posteriori’ ($\hat{\sigma}$) altimetric accuracies were compared. This model was derived from the altimetric differences in the terrain between both datasets. To reject outliers from the corrected model, we eliminated the points whose altimetric difference fell outside the 95 % confidence interval (St-Onge et al. 2008).

DTM, DSM and CHM generation

After the registration of both datasets, the different digital models relating to terrain (DTM), surface (DSM) and canopy (CHM) were obtained by surface generation in the form of triangular meshes from the resulting classified cloud. These meshes had to be filtered and refined to remove the errors generated during the automated process.

This step used the approximation of Attene (2010), which incorporates several automated and sequential tasks:

- Filling of holes through algorithms of planar triangulations (Barequet and Sharir 1995) or more complex approaches based on interpolation of the radial basis function (Branch et al. 2006), the minimum distance (Dolenc and Makela 1993) and the measurement of angles (Bøhn and Wozny 1992; Varnuška et al. 2005).
- Repair of meshing gaps, based on minimum threshold distance algorithms (Rock and Wozny 1992; Barequet and Kumar 1997).
- Removal of topological noise, allowing the mesh to be re-triangulated locally (Guskov and Wood 2001).
- Removal of geometric noise by algorithms that apply filters as anti-aliased Laplacians in general or specific zones (Fan et al. 2008).

Finally, the CHM was obtained from the difference between the photogrammetrical DSM and the DTM resulting from the fusion of the point clouds (Järnstedt et al. 2012). The CHM represents the normalised heights of the vegetation with respect to the surface of the terrain, with a planimetric resolution of 1 m (D'Oliveira et al. 2012).

Experimental results

This study was conducted in an area of public land in the municipality of Bienservida in the province of Albacete (Spain). In particular, the study zone is located on land identified in the Public Usefulness Catalogue as No. 26. Figure 5a shows a map with the location of the study zone outlined in white. The scrubland area covers 1100 Ha. This is of great interest from a forestry perspective because the densely forested zone hosts a forest mass composed of

Pinus nigra with different fractions of coverage according to the National Forest Inventory of Spain. The area also has a steep topography, and thus photogrammetric surveys are more appropriate from a practical point of view than classic forestry methods. The choice of this zone was also based on the availability of a pre-existing work plan that included the selected land and incorporated a classic forestry inventory. Thus, we established a zone of 2.00 km² (Fig. 5b) as the study area where we could apply the proposed methodology.

Regarding the LiDAR dataset, despite its official source, it was necessary to validate the data in advance by visual checking and manual refining. As a result, some outliers such as 'vegetation' or 'noise' were classified as 'ground', whereas some buildings were classified as 'vegetation'. To contrast changes in the LiDAR cloud with the initial classification, a confusion matrix was developed. A total of 4,822,511 points were classified correctly, obtaining a global accuracy of 99.98 %. An analysis of the confusion matrix, including the errors of commission and omission as well as producer and user accuracy can be seen in Table 3. These results show the insignificance of the incorrectly classified points in relation to the entirety of the cloud. A 1 % error was only exceeded by the 'others' class due to the presence of incorrect ground and vegetation points.

To perform photogrammetric data acquisition, the flight over the study area was planned with a height of 300 m, corresponding to a 7.50-cm GSD. The camera shooting interval was configured according to the minimum forward overlap and flight speed to meet the flight planning requirements and avoid image blurring, respectively (see "Flight planning and execution" section for more details). The obtained flight plan is outlined in Fig. 6, in which the rectangles represent the footprint of each image (area covered on the ground) resulting from each camera position (circles) along the flight strips. These footprints were

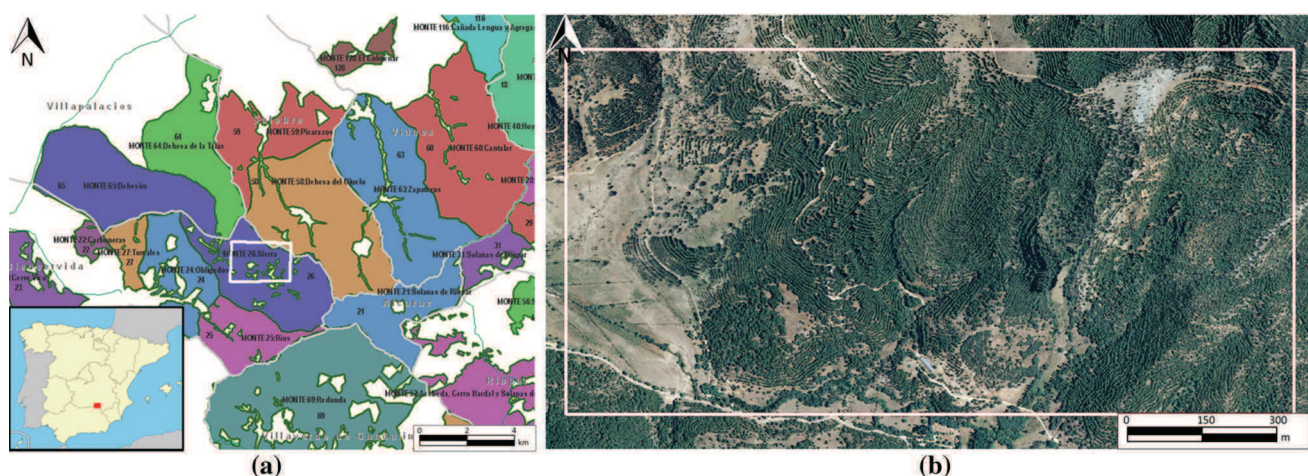


Fig. 5 **a** Location map with a box around the study area (white rectangle) and **b** orthophoto of the study area (EPSG code 25830)

Table 3 (a) Confusion matrix from the LiDAR data considering ‘ground’ and ‘vegetation’ classes and (b) errors of commission and omission and user and producer accuracy

	Refined LiDAR Data			
	Vegetation	Ground	Others	
(a)				
<i>Initial LiDAR data</i>				
Vegetation	3,674,535	0	325	3,674,860
Ground	517	1,145,807	20	1,146,344
Others	0	0	2169	2169
	3,675,052	1,145,807	2514	4,823,373
	Commission %	Omission %	Producer accuracy	User accuracy
(b)				
Vegetation	0.009	0.014	99.991	99.986
Ground	0.047	0.000	99.953	100.000
Others	0.000	13.723	100.000	86.277
	Global accuracy: 99.982 %			



Fig. 6 Flight planning, 0.08 m GSD: *rectangles* represent the footprint of each image, and circles are the camera positions along the flight strips (EPSG code 25830)

projected based on the DTM ground relief to verify compliance with the flight parameter requirements.

The flight was carried out on 5 December 2013, covering a greater area than proposed to ensure total coverage of the study area. The flight run followed the established plan. Finally, images were georeferenced according to ETRS89 UTM 30 North (Coordinate Reference System, CRS EPSG code 25830), which is required by Spanish legislation for all geomatic products. The Albacete station was taken as a reference from the ERGNSS network (network of permanent geodetic GNSS stations of the National Geographic Institute of Spain) and used to correct

the position of the RTK solution. In the navigation phase, which used a GNSS, WGS84 CRS was employed (EPSG code 4326). This georeferencing served as a preliminary photogrammetric adjustment and helped the process of computational matching.

Before the flight, 29 artificial ground points were placed in the zone to be measured by GNSS; these acted as control and check points. A georeferencing precision of 0.05 m was obtained in GNSS measurement post-processing.

In the conventional photogrammetric processing method carried out according to “[Low-cost photogrammetric workflow](#)” section, a total of 12,732,877 matching points were obtained, detecting 2,399,164 outliers through a robust estimation of the fundamental matrix (Barazzetti et al. 2010). The generated 3D dense model (Fig. 7) was composed of 290 million points after the processing of 1001 images, which is a density of 145 points/m². The model was georeferenced using 17 ground control points, obtaining an absolute georeferencing error of 1.21 m from the check points.

Once the photogrammetric point cloud had been generated, it was necessary to classify the points according to two classes: ground and vegetation. To distinguish the vegetation, radiometric segmentation was carried out, taking advantage of the visible spectrum of the photogrammetric point cloud. Figure 8 shows an example of the results of this processing.

Next, geometric segmentation was performed, working with the non-vegetation class, which was re-labelled ‘ground’. The resulting photogrammetric point cloud classification is outlined in Table 4.

To analyse the statistical compatibility of both data sources (LiDAR and photogrammetry), the accuracies of both sets of registrations were compared. The ‘a priori’ accuracy was $\sigma = 0.41$ m (Eq. 2) while the ‘a posteriori’ accuracy obtained was $\hat{\sigma} = 0.47$ m, being the mean altimetric accuracy 0.17 m, confirming the validity of the results. These values were acquired in areas sharing common ground points between the LiDAR and refined photogrammetric point clouds, thus generating an altimetric difference map.

$$\sigma_{\text{fusion}} = \sqrt{(\sigma_{\text{photogrammetry}}^2 + \sigma_{\text{LiDAR}}^2)}$$

$$\sigma_{\text{fusion}} = \sqrt{(0.10^2 + 0.40^2)} = 0.41 \text{ m} \quad (2)$$

On the map of altimetric differences, we removed the values that fell outside a 95 % confidence interval, and the remaining differences were interpolated to obtain values at points lacking photogrammetric terrain data. Figure 9 shows a Q–Q plot of the map’s height differences compared with standard normal quantiles, demonstrating a non-Gaussian distribution of the errors (absence of

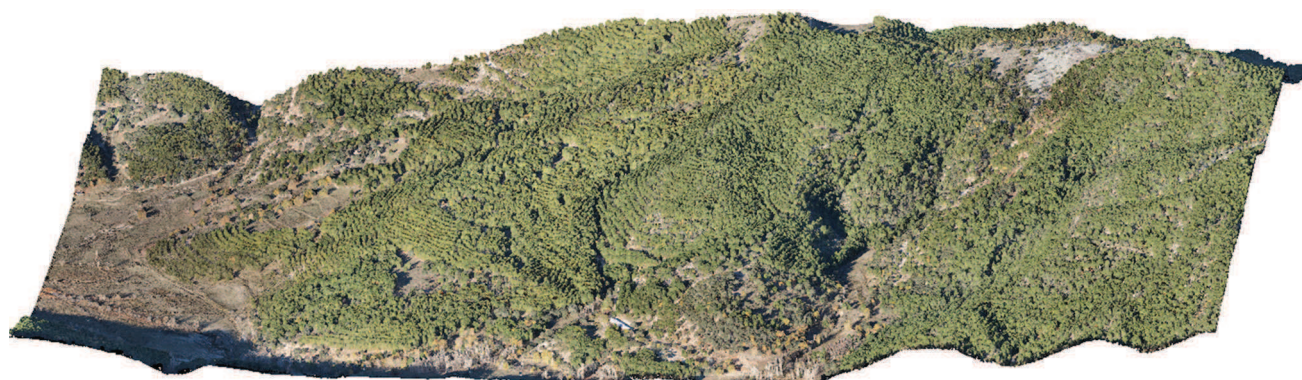


Fig. 7 Photogrammetric dense point cloud of the study area (145 points/m²)

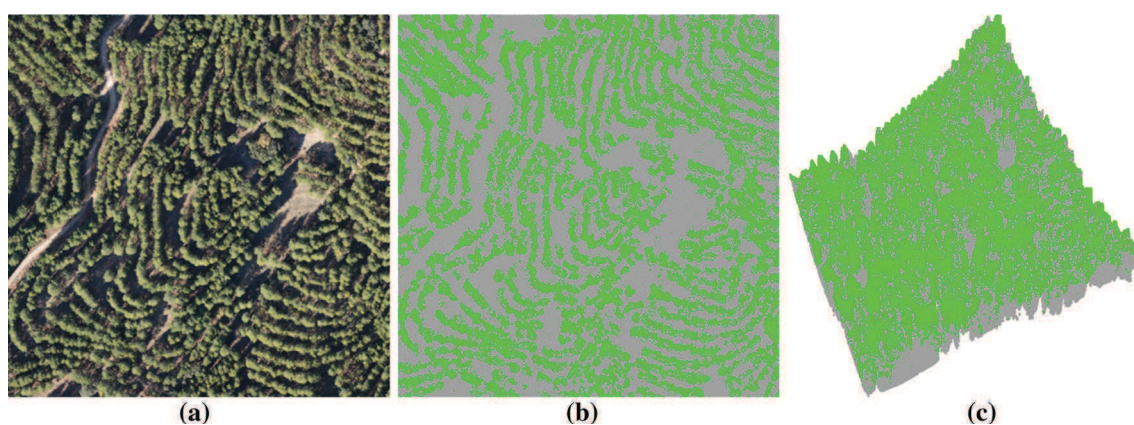


Fig. 8 Examples of radiometric segmentation of the photogrammetric point cloud. **a** Photogrammetric point cloud, **b** classified vegetation (green), **c** 3D classification view

Table 4 Classification of the photogrammetric cloud

Classification	No. points	%
Ground	29,281,752	17.70
Vegetation	135,562,812	81.92
Noise	528,961	0.32
Building	86,378	0.05
Wire conductor	12,668	0.01
Tower	2479	0.00

systematism), with some values that exceed the estimated accuracy. This is because the georeferencing of the LiDAR and photogrammetric data was not very rigorous owing to the scant topographic support of the LiDAR data, the automated matching processes, the use of low-accuracy inertial sensors and GNSS, and the use of non-metric cameras for the low-cost photogrammetry. Owing to this distribution, upon applying a solid-rigid transformation whose principal component is translation on the z axis, the error committed at certain points would be increased. Table 5 shows the map's statistical parameters and values.

In light of the above, we designed a discrete *correction model* (section “[Fusion of point clouds](#)”) that improved the accuracy of the registration based on the altimetric differences map. The model was applied to LiDAR terrain data at points lacking photogrammetric information by means of a computer application designed for this end, as shown in Fig. 10. These corrected points were included in the photogrammetric point cloud, thus obtaining the fused point cloud.

Once both datasets had been fused, the properties of the final point cloud were analysed, checking for the absence of vegetation points with negative height. Table 6 shows the number of points belonging to each class together with the range of elevations and height normalised with respect to the ground class. Figure 11 shows the final point cloud for vegetation, ground and building classifications, seen in plan view.

As final results, Figs. 12, 13 and 14 show the Digital Terrain, Surface and Canopy Models obtained from the hybrid cloud, rasterised with a mesh size of 1 m.

After analysis of the CHM, we observed that there were very few cases in which the vegetation surpassed a height of 20 m. The *P. nigra* specimens in the zone were between 20 and 23 m in height. There was one case in which a

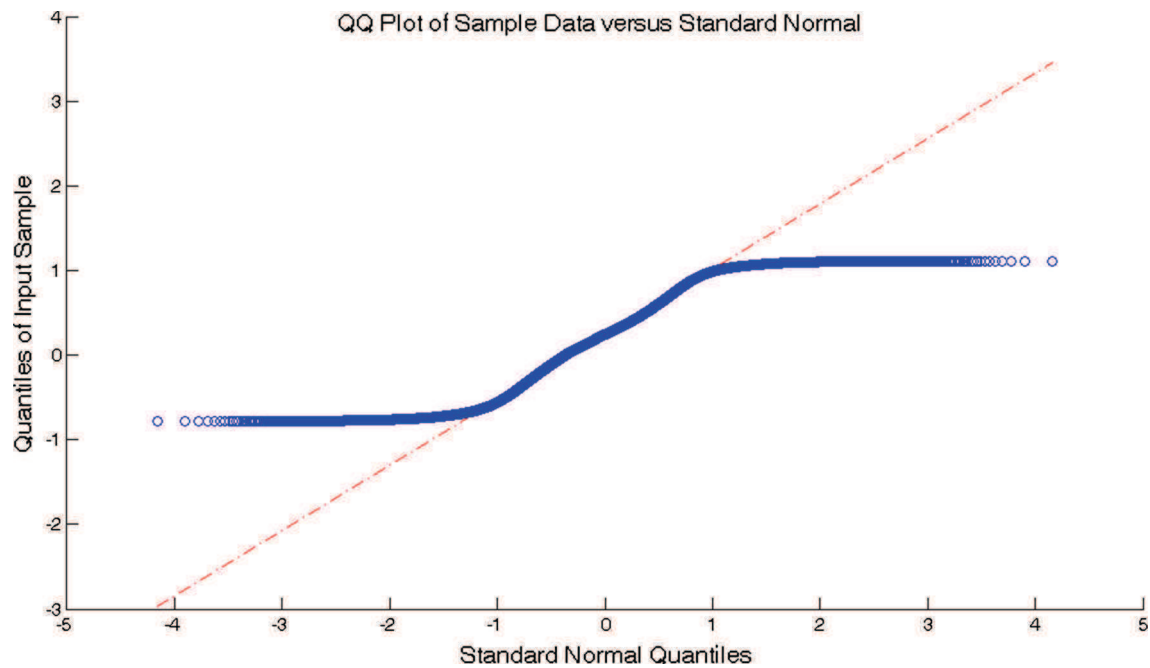


Fig. 9 Q–Q plot of the altimetric difference map versus standard normal quantiles

Table 5 Statistical data of the altimetric differences map

Maximum (m)	1.090
Mean (m)	0.226
Minimum (m)	−0.760
Std. deviation (m)	0.364

height of 27.7 m was attained, but this specimen was not a pine and was deciduous; it was probably a poplar, whose heights can reach 35 m.

The results allowed us to explore the development of forest growth in the area. To accomplish this, we analysed

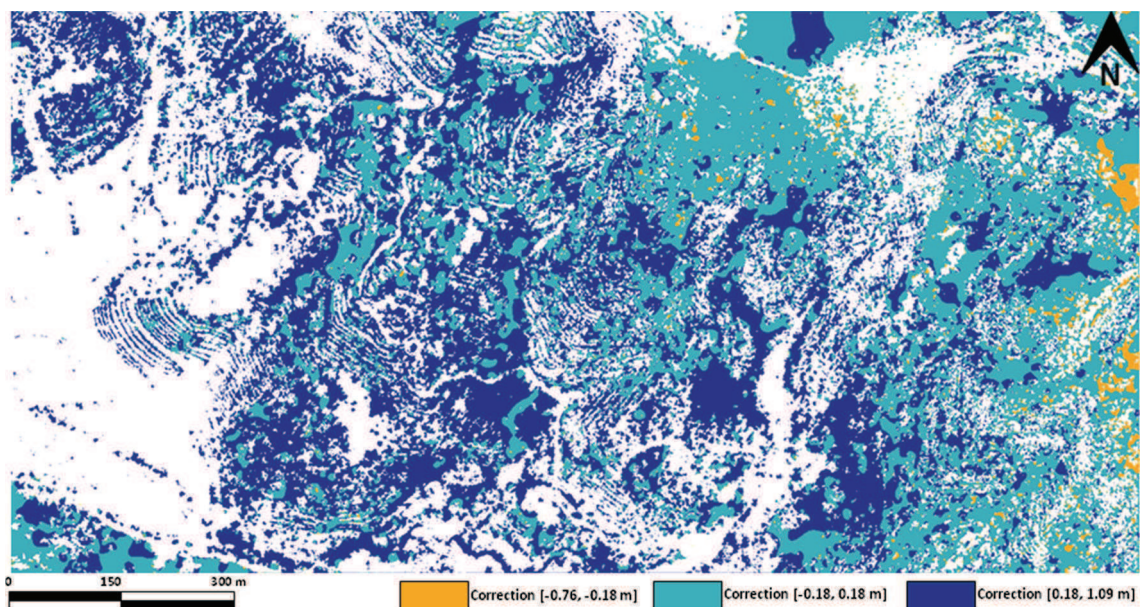
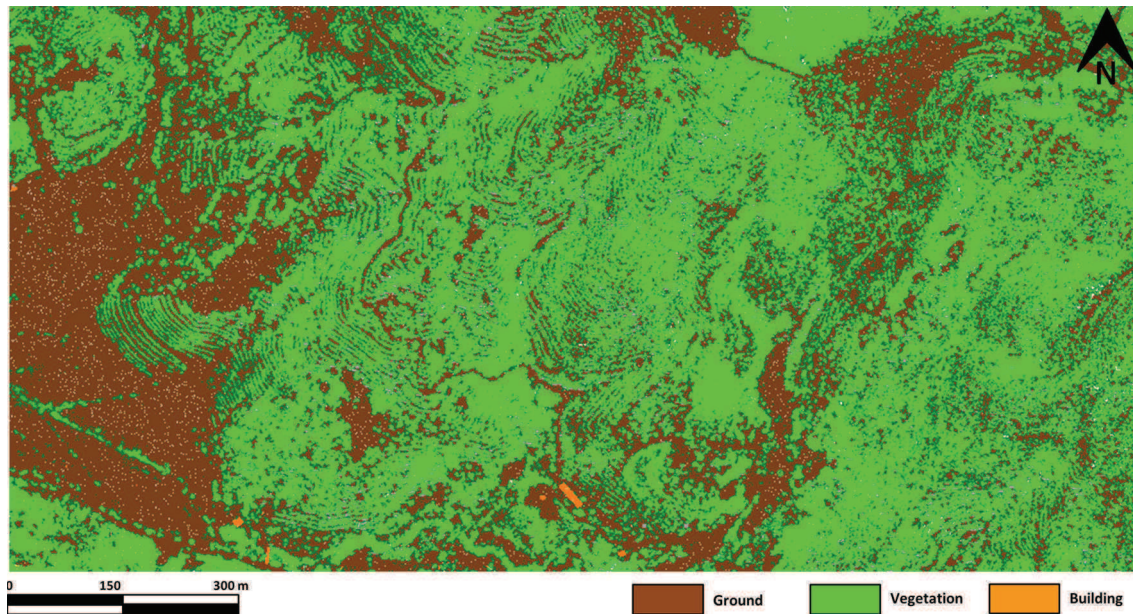
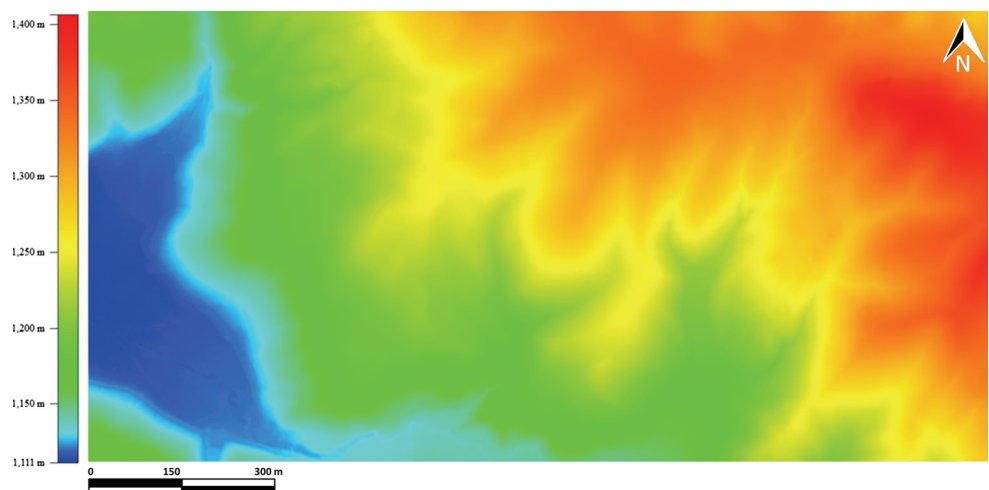


Fig. 10 Correction model coded by colour (EPSG code 25830)

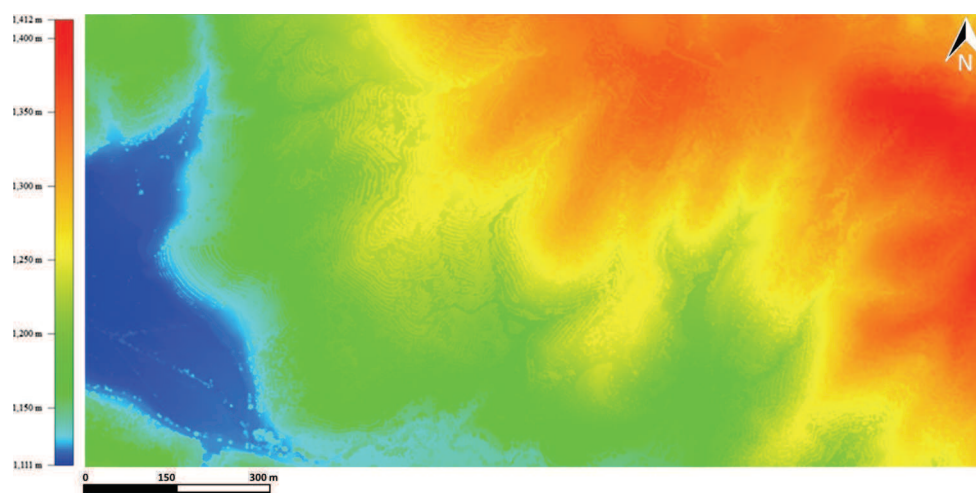
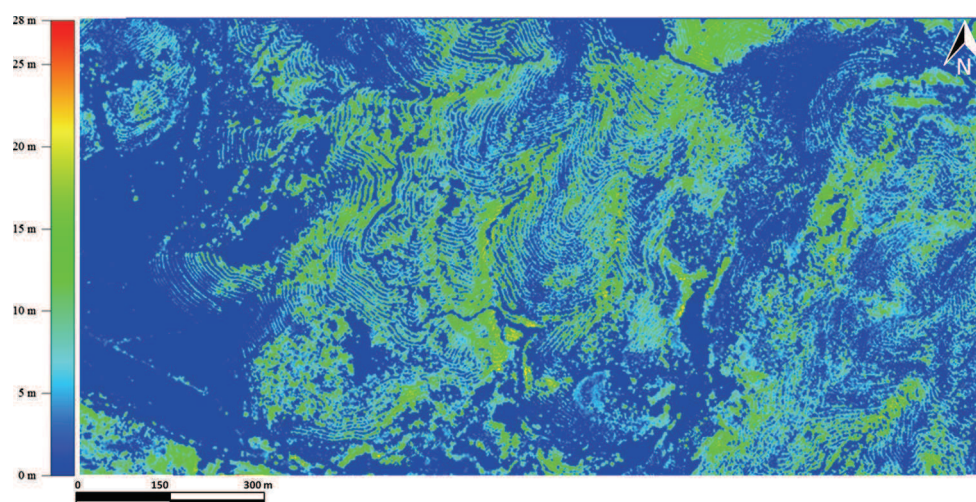
Table 6 Classification of the final fusion cloud

Classification	No. points	%	Z_Min (m)	Z_Max (m)	Height (m)
Ground	29,220,875	17.78	1111.24	1406.59	0
Low vegetation	22,638,874	13.78	1111.50	1407.50	(0–1]
Medium vegetation	17,920,617	10.91	1112.68	1409.46	[1–3]
High vegetation	93,514,449	56.93	1113.50	1412.49	[3–27.67]
Building	86,378	0.05	1119.99	1184.34	–
Others	911,914	0.55	–	–	–

**Fig. 11** Plan view of the final classified fusion cloud**Fig. 12** Digital terrain model

the distribution of the differences in plant volume between the CHM from the LiDAR data taken in 2009 and that generated from the hybrid point cloud in late 2013, both with respect to their respective DTMs. The increase in

biomass volume that occurred during the interim was 3,318,501 m³ in the 2.00 km² study area. This was due to the protectionist legislation enacted in the zone during those years (Cerro and Borja 2007).

Fig. 13 Digital surface model**Fig. 14** Canopy height model

Conclusions

This paper describes a successful methodology that generates a Canopy Height Model for conducting forest inventories such a stratification of forest masses to forest management unit applications or a stock calculation and for fire studies obtaining combustible models. This CHM permits a better understanding of the forest structure in detail, allowing to know the relationships between the flora, the fauna and the soil over large extensions. The combined use of low-cost photogrammetry based on the use of economical, conventional, non-metric digital cameras and aerial LiDAR open data, together with the use of the latest computational vision techniques and geomatic tools, provides useful information for forestry applications.

In particular, by integrating the terrain data in the photogrammetric cloud, it is possible to incorporate LiDAR's capacity for terrain detection in zones of dense vegetation with the greater spatial, radiometric and temporal resolution of low-cost photogrammetry from alternative

platforms such as the aerial trike or RPAS. Moreover, these platforms allow the loading of sensors suitable for vegetation analysis, depending on their payload capacity. Thus, it is possible to carry out a radiometric classification of the vegetation that improves upon current morphological methods. In this sense, we define a correction model that allows LiDAR data to be adjusted to the photogrammetric point cloud, obtaining an altimetric accuracy of 0.47 m for the registration data.

The advantage offered by this methodology is that it allows a CHM to be obtained with adequate phenological detail due to the combination of LiDAR flights performed at low temporal resolution and low-cost photogrammetric flights performed with the required periodicity. This also allows a reduction in the errors that arise in dasometric assessments upon incorporating models for the prediction of vegetation growth.

It is worth noting that the statistical compatibility of both sources of data could be improved in the data acquisition phase with appropriate field topographic support.

That is, photogrammetric point cloud georeferencing can be improved by designing pre-signalling targets of suitable colour for forestry applications and for later measurement in the images collected. It might even be possible to improve the targets' design to facilitate their detection and the automated extraction of the centroid. Another proposal would involve the incorporation of metric cameras, although in the case of RPAS this depends on the platform's payload capacity. This would increase both the associated cost and the accuracy.

The proposed methodology reduces the time required for acquisition and processing compared with that of traditional techniques of forest inventorying, with the added advantage that it provides vectorial information in the form of classified point clouds. This implies an increase in final accuracy at the rodal level and simplified integration and management of forestry information in Geographic Information Systems. At the same time, the subjectivity associated with operator-generated uncertainty is removed. Needless to say that the complementarity of both techniques would offer to reach better results, taking advantages of the spatial continuity of the remote sensing in order to extrapolate the manual measurements of the trees.

In future work, we shall address the forestry variables in the obtained dense cloud and perform a comparative study with the variables obtained from the LiDAR information, applying rodal, individual-tree or even a combination of both methods to benefit from the high resolution of the initial data. To date, from the obtained CHM, essential tree parameters such as diameter at breast height (DBH) or distinguishing between species are not reliably derived yet. Another line of enquiry will be to contrast the variables obtained from the dense cloud with other data from a classic inventory of the study zone, i.e., the National Forest Inventory of Spain and the inventory drafted by the Public Land and Natural Spaces Service of the Agricultural Commission of the Regional Government of Castilla-La Mancha, Spain.

Author contribution statement B.F.-G., D.H.-L. and D.G.-A. planned the experiment and supervised processing, M.H.-H., B.F.-G. and S.B.-L. performed the study, analysed data and prepared the manuscript and P.R.-G. contributed to data interpretation. All authors wrote the manuscript.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

- ASPRS Foundation (2012) LASer (LAS) file format exchange activities. <http://www.asprs.org/Committee-General/LASer-LAS-File-Format-Exchange-Activities.html>. Accessed 01 Nov 2014
- Attene M (2010) A lightweight approach to repairing digitized polygon meshes. *Vis Comput* 26(11):1393–1406
- Axelsson P (1999) Processing of laser scanner data—algorithms and applications. *ISPRS J Photogramm Remote Sens* 54(2):138–147
- Barazzetti L, Remondino F, Scaioni M, Brumana R (2010) Fully automatic UAV image-based sensor orientation. In: *Proceedings of the 2010 Canadian geomatics conference and symposium of commission I*
- Barequet G, Kumar S (1997) Repairing CAD models. In: *Visualization'97, proceedings*, pp 363–370. IEEE
- Barequet G, Sharir M (1995) Filling gaps in the boundary of a polyhedron. *Comput Aided Geom Des* 12(2):207–229
- Benko M, Balenovic I (2011) Past, present and future of application of remote sensing methods in croatian forest inventory. *Sumarski List* 135:272–281
- Bohlin J, Wallerman J, Fransson JES (2012) Forest variable estimation using photogrammetric matching of digital aerial images in combination with a high-resolution DEM. *Scand J For Res* 27(7):692–699
- Bøhn JH, Wozny MJ (1992) Automatic CAD-model repair: shell-closure. In: *Proceedings of symposium on solid freeform fabrication*, pp 86–94
- Branch D, Dang LC, Hall N, Ketchum W, Melakayil M, Parrent J, Baron E (2006) Comparative direct analysis of type Ia supernova spectra. II. Maximum light. *Publ Astron Soc Pac* 118(842):560–571
- Cerro A, Borja MEL (2007) El “Pinus nigra arn.” en la Serranía de Cuenca: estudio sobre su regeneración natural y bases para su gestión. Junta de Comunidades de Castilla-La Mancha, Dirección General del Medio Ambiente
- Chauve A, Mallet C, Bretar F, Durrieu S, Deseilligny MP, Puech W (2007) Processing full-waveform lidar data: modelling raw signals. In: *International archives of photogrammetry, remote sensing and spatial information sciences*, pp 102–107
- CNIG (National Center of Geographic Information in Spain) (2009) Technical specifications for the National Plan of Aerial Orthophotography (PNOA). <ftp://pnoa.ign.es>. Accessed 01 Nov 2014
- CNIG (National Center of Geographic Information in Spain) (2015). <http://centrodedescargas.cnig.es/CentroDescargas/>. Accessed 16 July 2015
- Dolenc A, Makela I (1993) Some efficient procedures for correcting triangulated models. In: *Proceedings of solid freeform fabrication symposium*, pp 126–134
- D'Oliveira MV, Reutebuch SE, McGaughey RJ, Andersen HE (2012) Estimating forest biomass and identifying low-intensity logging areas using airborne scanning lidar in Antimary State Forest, Acre State, Western Brazilian Amazon. *Remote Sens Environ* 124:479–491
- Eid T, Gobakken T, Naesset E (2004) Comparing stand inventories for large areas based on photo-interpretation and laser scanning by means of cost-plus-loss analyses. *Scand J For Res* 19(6):512–523

- Estornell J, Ruiz LA, Velazquez-Marti B, Hermosilla T (2012) Assessment of factors affecting shrub volume estimations using airborne discrete-return LiDAR data in Mediterranean areas. *J Appl Remote Sens* 6(1):063544
- Fan YZ, Tam BS, Zhou J (2008) Maximizing spectral radius of unoriented Laplacian matrix over bicyclic graphs of a given order. *Linear Multilinear Algebra* 56(4):381–397
- Gleason CJ, Im J (2012) Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sens Environ* 125:80–91
- Gonzalez E, Dieguez U, Miranda D (2012) Estimation of stand variables in *Pinus radiata* D. Don plantations using different LiDAR pulse densities. *Forestry* 85(2):281–292
- González-Aguilera D, Guerrero D, Hernández-López D, Rodríguez-González P, Pierrot M, Fernández-Hernández J (2013) PW, photogrammetry workbook
- González-Ferreiro E, Diéguez-Aranda U, Crecente-Campo F, Barreiro-Fernández L, Miranda D, Castedo-Dorado F (2014) Modelling canopy fuel variables for *Pinus radiata* D. Don in NW Spain with low-density LiDAR data. *Int J Wildl Fire* 23(3):350–362
- Gupta S, Weinacker H, Koch B (2010) Comparative analysis of clustering-based approaches for 3-D single tree detection using airborne fullwave lidar data. *Remote Sens* 2(4):968–989
- Guskov I, Wood ZJ (2001) Topological noise removal. In: 2001 graphics interface proceedings, Ottawa, Canada, 19
- Hernández-Lopez D, Felipe B, González D, Arias B (2013) An automatic approach to UAV flight planning and control for photogrammetric applications: a test case in the Asturias Region (Spain). *Photogramm Eng Remote Sens* 79(1):87–98
- Hyypä J, Hyypä H, Leckie D, Gougeon F, Yu X, Maltamo M (2008) Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *Int J Remote Sens* 29(5):1339–1366
- IGN (2015) <http://pnoa.ign.es/presentacion>. Accessed 16 July 2015
- Jaakkola A, Hyypä J, Kukko A, Yu X, Kaartinen H, Lehtomäki M, Lin Y (2010) A low-cost multi-sensoral mobile mapping system and its feasibility for tree measurements. *ISPRS J Photogramm Remote Sens* 65:514–522
- Järnstedt J, Pekkarinen A, Tuominen S, Ginzler C, Holopainen M, Viitala R (2012) Forest variable estimation using a high-resolution digital surface model. *ISPRS J Photogramm Remote Sens* 74:78–84
- Kankare V, Vastaranta M, Holopainen M, Rättyä M, Yu X, Hyypä J, Viitala R (2013) Retrieval of forest aboveground biomass and stem volume with airborne scanning LiDAR. *Remote Sens* 5(5):2257–2274
- Kohavi R, Provost F (1998) Glossary of terms. *Mach Learn* 30(2–3):271–274
- Kraus K (2007) *Photogrammetry, 2007. Geometry from images and laser scans*. Walter de Gruyter
- Lim KS, Treitz PM (2004) Estimation of above ground forest biomass from airborne discrete return laser scanner data using canopy-based quantile estimators. *Scand J For Res* 19(6):558–570
- Lisein J, Pierrot M, Bonnet S, Lejeune P (2013) A photogrammetric workflow for the creation of a forest canopy height model from small unmanned aerial system imagery. *Forests* 4(4):922–944
- Lowe DG (2004) Distinctive image features from scale-invariant keypoints. *Int J Comput Vis* 60:91–110
- Magnussen S, Boudewyn P, Wulder MA, Seemann D (2000) Predictions of forest inventory cover type proportions using landsat TM. *Silva Fennica* 34(4):351–370
- Magnussen S, Naesset E, Wulder MA (2007) Efficient multiresolution spatial predictions for large data arrays. *Remote Sens Environ* 109(4):451–463
- Magnusson M, Fransson JES, Olsson H (2007) Aerial photo-interpretation using Z/I DMC images for estimation of forest variables. *Scand J For Res* 22(3):254–266
- Mallet C, Bretar F (2009) Full-waveform topographic lidar: state-of-the-art. *ISPRS J Photogramm Remote Sens* 64(1):1–16
- Means JE, Acker SA, Fitt BJ, Renslow M, Emerson L, Hendrix CJ (2000) Predicting forest stand characteristics with airborne scanning lidar. *Photogramm Eng Remote Sens* 66(11):1367–1372
- Mora B, Wulder MA, Hobart GW, White JC, Bater CW, Gougeon FA, Coops NC (2013) Forest inventory stand height estimates from very high spatial resolution satellite imagery calibrated with lidar plots. *Int J Remote Sens* 34(12):4406–4424
- Naesset E (1997) Estimating timber volume of forest stands using airborne laser scanner data. *Remote Sens Environ* 61(2):246–253
- Naesset E (2004) Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. *Scand J For Res* 19(2):164–179
- Naesset E, Bollandsas OM, Gobakken T (2005) Comparing regression methods in estimation of biophysical properties of forest stands from two different inventories using laser scanner data. *Remote Sens Environ* 94(4):541–553
- Navarro-Cerrillo RM, del Campo AD, Ceacero CJ, Quero JL, Hermoso de Mena J (2014) On the importance of topography, site quality, stock quality and planting date in a semiarid plantation: feasibility of using low-density LiDAR. *Ecol Eng* 67:25–38
- NavCen (2008) Global positioning system standard positioning service performance standar, 4th edn. US Department of Defense: Position, Navigation and Timing Executive Committee, Washington
- Nelson R, Krabill W, Tonelli J (1988) Estimating forest biomass and volume using airborne laser data. *Remote Sens Environ* 24(2):247–267
- Nelson R, Oderwald R, Gregoire TG (1997) Separating the ground and airborne laser sampling phases to estimate tropical forest basal area, volume, and biomass. *Remote Sens Environ* 60(3):311–326
- Nelson R, Parker G, Hom M (2003) A portable airborne laser system for forest inventory. *Photogramm Eng Remote Sens* 69(3):267–273
- Ortega-Terol D, Moreno MA, Hernández-López D, Rodríguez-González P (2014) Survey and classification of large woody debris (LWD) in streams using generated low-cost geomatic products. *Remote Sens* 6:11770–11790
- Pierrot-Deseilligny M, Clery I (2011) An open source bundle adjustment software for automatic calibration and orientation of set of images. In: *Apero, ISPRS symposium, 3DARCH11*, Trento, Italy, March 2–4, pp 269–276
- Popescu SC, Wynne RH, Nelson RF (2002) Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. *Comput Electron Agric* 37(1):71–95
- Premierlani W, Bizard P (2014) Direction cosine matrix IMU: theory. <http://gentlenav.googlecode.com/files/DCMDraft2.pdf>. Accessed 20 Dec 2014
- Richardson JJ, Moskal LM (2011) Strengths and limitations of assessing forest density and spatial configuration with aerial LiDAR. *Remote Sens Environ* 115(10):2640–2651
- Rock SJ, Wozny MJ (1992) Generating topological information from a bucket of facets. In: *Solid freeform fabrication symposium proceedings*, pp 251–259. The University of Texas at Austin, Austin
- St-Onge B, Vega C, Fournier RA, Hu Y (2008) Mapping canopy height using a combination of digital stereo-photogrammetry and lidar. *Int J Remote Sens* 29(11):3343–3364

- Takasu T (2009) RTKLIB: open source program package for RTK-GPS. FOSS4G, Tokyo, Japan
- Tao W, Lei Y, Mooney P (2011) Dense point cloud extraction from UAV captured images in forest area. In: Proceedings of the 2011 IEEE international conference on spatial data mining and geographical knowledge services (ICSDM), pp 389–392
- Varnuška M, Parus J, Kolingerová I (2005) Simple holes triangulation in surface reconstruction. In: Proceedings of ALGORITMY, pp 280–289
- Wallace L, Lucieer A, Watson C, Turner D (2012) Development of a UAV-LiDAR system with application to forest inventory. *Remote Sens* 4:1519–1543
- Wang Z, Boesch R, Ginzler C (2007) Color and lidar data fusion: application to automatic forest boundary delineation in aerial images. *Int Arch Photogramm Remote Sens Spat Inf Sci [CD]* 36(1):W51
- Weinacker H, Koch B, Heyder U, Weinacker R (2004) Development of filtering, segmentation and modelling modules for lidar and multispectral data as a fundament of an automatic forest inventory system. *Int Arch Photogramm Remote Sens Spat Inf Sci* 36(Part 8):50–55
- White JC, Wulder MA, Varhola A, Vastaranta M, Coops NC, Cook BD, Woods M (2013a) A best practices guide for generating forest inventory attributes from airborne laser scanning data using an area-based approach. *For Chron* 89(6):722–723
- White JC, Wulder MA, Vastaranta M, Coops NC, Pitt D, Woods M (2013b) The utility of image-based point clouds for forest inventory: a comparison with airborne laser scanning. *Forests* 4(3):518–536
- Willers JL, Wu J, O'Hara C, Jenkins JN (2012) A categorical, improper probability method for combining NDVI and LiDAR elevation information for potential cotton precision agricultural applications. *Comput Electron Agric* 82:15–22
- Wulder MA, White JC, Fournier RA, Luther JE, Magnussen S (2008a) Spatially explicit large area biomass estimation: three approaches using forest inventory and remotely sensed imagery in a GIS. *Sensors* 8(1):529–560
- Wulder MA, White JC, Hay GJ, Castilla G (2008b) Towards automated segmentation of forest inventory polygons on high spatial resolution satellite imagery. *For Chron* 84(2):221–230
- Wulder MA, White JC, Nelson RF, Næsset E, Ørka HO, Coops NC, Gobakken T (2012) Lidar sampling for large-area forest characterization: a review. *Remote Sens Environ* 121:196–209
- Wulder MA, Coops NC, Hudak AT, Morsdorf F, Nelson R, Newnham G, Vastaranta M (2013) Status and prospects for LiDAR remote sensing of forested ecosystems. *Can J Remote Sens* 39(-sup1):S1–S5

IV. CONCLUSIONES Y PERSPECTIVAS FUTURAS

4. CONCLUSIONES Y PERSPECTIVAS FUTURAS

En esta Tesis Doctoral se han realizado aportaciones en líneas de investigación que avanzan en la dirección de la aplicación de la fotogrametría de bajo coste y rango cercano a la Ingeniería Agroforestal. Se trata de una técnica no destructiva y no invasiva idónea para inspeccionar y monitorizar cultivos y superficies forestales, mediante una óptima modelización de parámetros biofísicos y extrayendo información con rigor métrico y georreferenciada.

Esta Tesis Doctoral es el resultado de un compendio de tres artículos científicos publicados en revistas de impacto especializadas. A continuación se reseñan las conclusiones obtenidas y se proponen las líneas futuras de investigación vinculadas a los diferentes artículos.

El **primer artículo** describe una metodología eficaz para la calibración radiométrica mediante el método vicario de la cámara multispectral TetraCam miniMCA, embarcada en una plataforma aérea tripulada del tipo paramotor y usando tarjetas de bajo coste de material de reflectividad invariante. La potencialidad del sistema es evidente al poder embarcar una gran cantidad de sensores que amplían los estudios multispectrales, beneficiado por una altura de vuelo que elimina la necesidad de correcciones atmosféricas. Los resultados confirman una nueva forma de fotogrametría multispectral de bajo coste y alta resolución espacial que junto con el uso de las últimas técnicas de herramientas geomáticas de código abierto generan imágenes multispectrales perfectamente georreferenciadas y calibradas radiométricamente. Pueden utilizarse para evaluar y clasificar con éxito grandes extensiones de diferentes cultivos, permitiendo tomar decisiones sobre el riego, el aporte nutricional y la evolución de la cosecha, así como la posibilidad de derivar magnitudes cuantitativas de índices de vegetación. Futuras investigaciones se ocuparán de la integración de las imágenes calibradas en modelos agronómicos para evaluar su compatibilidad con las variables biofísicas significativas del cultivo, mejorando así la productividad de la cosecha en términos cuantitativos y cualitativos.

En el **segundo artículo** se presenta un método no invasivo de bajo coste con aplicación a la viticultura de precisión consistente en estimar la producción de uva del viñedo. Se trata de un método rápido, fiable, robusto y objetivo que sirve para la toma de decisiones con suficiente antelación en la gestión del viñedo, predecir resultados y planificar la vendimia de forma óptima. El método desarrollado se apoya en la adaptación para este estudio de la herramienta software PW, que permite la reconstrucción métrica y análisis dimensional de racimos de viñedos a partir de la toma de imágenes en campo de cada una de las cepas. Las ventajas de PW abarcan la automatización del proceso, la calidad al generar modelos densos de resolución equivalente al tamaño del píxel de la imagen, y por último un bajo coste y sencillez de manejo. Como perspectivas futuras se tratará de abordar el tema de la compacidad y su relación con las diferencias de volúmenes, característica clave que influye de manera importante en la calidad de la uva y, consecuentemente, del vino. Otra de las líneas de acción futuras pasa por diseñar y construir una plataforma que sustente la configuración de las tomas fotográficas y que pueda ser embarcada en una plataforma móvil del tipo quad o sistema terrestre robotizado.

El **tercer artículo** desarrolla una metodología para conseguir Modelos Digitales de Altura de Cubierta Vegetal destinados al inventario forestal basada en la integración de datos LiDAR y fotogramétricos. El flujo de trabajo propuesto incorpora las ventajas de la capacidad de detección del terreno procedente de la tecnología LiDAR en zonas de vegetación densa, con la mayor resolución espacial, radiométrica y temporal de la fotogrametría de bajo coste desde plataformas alternativas como el paramotor. El gran avance que supone esta metodología es que permite obtener un Modelo Digital de Altura de Cubierta Vegetal en el momento o estado fenológico adecuado gracias a la combinación de vuelos LiDAR realizados con baja resolución temporal y vuelos fotogramétricos de bajo coste efectuados con la periodicidad necesaria. Como líneas futuras, se plantea estimar las variables dasométricas forestales a partir de la nube densa obtenida y realizar una comparativa con las variables obtenidas a partir de la información LiDAR, o incluso con datos de inventarios clásicos.

Concluyendo de manera general la investigación, se verifica que la fotogrametría de bajo coste y rango cercano aplicada a la Ingeniería Agroforestal proporciona información válida para una gestión óptima, disminuyendo el tiempo de campo y el coste asociado, así como una mejora en la precisión, calidad y cantidad de los resultados obtenidos.

REFERENCIAS BIBLIOGRÁFICAS

REFERENCIAS BILIOGRÁFICAS

Aguilar, M. A., Pozo, J. L., Aguilar, F. J., Sanchez-Hermosilla, J., Páez, F. C., & Negreiros, J. (2008). 3D surface modelling of tomato plants using close-range photogrammetry. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 330.

Akca, D & Gruen, A. (2007). *Generalized least squares multiple 3D surface matching*. Institute of Geodesy and Photogrammetry, ETH Zurich, 2007.

Attene, M. (2010). A lightweight approach to repairing digitized polygon meshes. *The Visual Computer*, 26(11), 1393-1406.

Barber, C. B., Dobkin, D. P., & Huhdanpaa, H. (1996). The quickhull algorithm for convex hulls. *ACM Transactionson Mathematical Software (TOMS)*, 22(4), 469-483.

Battany, M. (2008). A Practical Method for Counting Berries based on Image Analysis. 2nd Annual National Viticulture Research Conference, University of California, Davis, USA, 4-5, July 9-11, 2008.

Benko, M. and Balenovic, I., 2011. Past, present and future of application of remote sensing methods in croatian forest inventory. *Sumarski List*, 135, 272-281.

Blom, P. E., & Tarara, J. M. (2009). Trellis tension monitoring improves yield estimation in vineyards. *Hortscience*, 44(3), 678-685.

Bohlin, J.; Wallerman, J. and Fransson, J. E. S., 2012. Forest variable estimation using photogrammetric matching of digital aerial images in combination with a high-resolution DEM. *Scandinavian Journal of Forest Research*, 27(7), 692-699.

Cerro, A., Borja, M. E. L., 2007. El "Pinus nigra arn." en la Serranía de Cuenca: estudio sobre su regeneración natural y bases para su gestión. *Junta de Comunidades de Castilla-La Mancha, Dirección General del Medio Ambiente*.

Chauve, A., Mallet, C., Bretar, F., Durrieu, S., Deseilligny, M. P., & Puech, W. (2007, September). Processing full-waveform lidar data: modelling raw signals. In *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 2007* (pp. 102-107).

Chen, X., Zhao, H., Li, P. and Yin, Z., "Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes". *Remote Sensing of Environment*, 104(2), 133-146 (2006).

Chherawala, Y.; Lepage, R. & Doyon, G (2006). In Food Grading/Sorting Based on Color Appearance through Machine Vision: the Case of Fresh Cranberries, Information and Communication Technologies, 2006. *ICTTA '06. 2nd, 0-0 0*; pp. 1540-1545.

Chuvieco, E. and Huete, A., "Fundamentals of satellite remote sensing", *CRC Press Inc* (2009).

Clingeffer, P. R., Martin, S., Krstic, M., & Dunn, G. M. (2001). *Crop development, crop estimation and crop control to secure quality and production of major wine grape varieties: A national approach: Final report to Grape and Wine Research & Development Corporation*. Grape and Wine Research & Development Corporation.

Davranche, A., Lefebvre, G., and Poulin, B. "Radiometric normalization of SPOT-5 scenes: 6S atmospheric model versus pseudo-invariant features". *Photogrammetric Engineering & Remote Sensing*, 75(6), (2009).

DeLuca, J. G., Gall, W. E., Ciferri, C., Cimini, D., Musacchio, A., & Salmon, E. (2006). Kinetochore microtubule dynamics and attachment stability are regulated by Hec1. *Cell*, 127(5), 969-982.

Diago, M.-P.; Correa, C.; Millán, B.; Barreiro, P.; Valero, C. & Tardaguila, J. (2012). Grapevine Yield and Leaf Area Estimation Using Supervised Classification Methodology on RGB Images Taken under Field Conditions. *Sensors*, 12, 16988-17006.

Dingirard, M. and Slater, P. N., "Calibration of Space-Multispectral Imaging Sensors: A Review", *Remote Sensing of Environment* 68(3), 194-205 (1999).

D'Oliveira, M. V., Reutebuch, S. E., McGaughey, R. J. and Andersen, H. E., 2012. Estimating forest biomass and identifying low-intensity logging areas using airborne scanning lidar in Antimary State Forest, Acre State, Western Brazilian Amazon. *Remote Sensing of Environment*, 124, 479-491.

Dunn, G. M., & Martin, S. R. (2003). The current status of crop forecasting in the Australian wine industry. *ASVO Seminar Series: Grapegrowing at the Edge*, pp. 4-8.

Dunn, G. M., & Martin, S. R. (2004). Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest. *Australian Journal of Grape and Wine Research*, 10(3), 196-198.

Esposito, F., Rufino, G. and Moccia, A., "1st mini-UAV integrated hyperspectral/thermal electro-optical payload for forest fire risk management," *Proc. AIAA InfotechAerosp. Conf*, pp. 653-665 (2007)

Estornell, J.; Ruiz, L. A.; Velazquez-Marti, B. & Hermosilla, T. (2012): "Assessment of factors affecting shrub volume estimations using airborne discrete-return LiDAR data in Mediterranean areas". *Journal of Applied Remote Sensing*, 6.

Gleason, C. J., Im, J., 2012. Forest biomass estimation from airborne LiDAR data using machine learning approaches. *Remote Sensing of Environment*, 125, 80-91.

González-Aguilera, D., Guerrero, D., Hernández-López, D., Rodríguez-Gonzálvez, P., Pierrot, M., Fernández-Hernández, J., (2013). PW, Photogrammetry Workbench.

González-Ferreiro, E., Diéguez-Aranda, U., Crecente-Campo, F., Barreiro-Fernández, L., Miranda, D., & Castedo-Dorado, F. (2014). Modelling canopy fuel variables for *Pinus radiata* D. Don in NW Spain with low-density LiDAR data. *International Journal of Wildland Fire*, 23(3), 350-362.

Greven, M. (2007) Manual for yield forecasting in Sauvignon Blanc grapes. *Marlborough Wine Research Centre*.

Gupta, S., Weinacker, H., & Koch, B. (2010). Comparative analysis of clustering-based approaches for 3-D single tree detection using airborne fullwave lidar data. *Remote Sensing*, 2(4), 968-989.

Guskov, I., & Wood, Z. J. (2001). Topological noise removal. *2001 Graphics Interface Proceedings: Ottawa, Canada*, 19.

Hernández-López, D., Felipe-García, B., González-Piqueras, J., and Alcázar, G. V. "An approach to the radiometric aerotriangulation of photogrammetric images". *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(6), 883-893 (2011).

Hernandez-Lopez, D., Felipe-Garcia, B., Gonzalez-Aguilera, D. and Arias-Perez, B., "An Automatic Approach to UAV Flight Planning and Control for Photogrammetric Applications: A Test Case in the Asturias Region (Spain)", *Photogrammetric engineering and remote sensing*, 79(1), 87-98 (2013).

Herrero Langreo, A., Barreiro Elorza, P., Santamaria, D., Paz, M., Baluja, J., Ochagavia, H. (2010). Pixel classification through mahalanobis distance for identification of grapevine canopy elements on rgb images.

Herwitz, S. R., Johnson, L. F., Dunagan, S. E., Higgins, R. G., Sullivan, D. V., Zheng, J., Lobitz, B. M., Leung, J. G., Gallmeyer, B. A., Aoyagi M., Slye, R. E. and Brass, J. A., "Imaging from an unmanned aerial vehicle: agricultural surveillance and decision support". *Computers and Electronics in Agriculture*, 44, 49-61 (2004).

Hiscocks, P. D. and Eng, P., "Measuring Luminance with a Digital Camera," (2011).

Honkavaara, E., Arbiol, R., Markelin, L., Martinez, L., Cramer, M., Bovet, S., Chandelier, L., Ilves, R., Klonus, S., Marshal, P., Schläpfer, D., Tabor, M., Thom, C. and Veje, N., "Digital Airborne Photogrammetry—A New Tool for Quantitative Remote Sensing?—A State-of-the-Art Review On Radiometric Aspects of Digital Photogrammetric Images", *Remote Sensing* 1(3), 577-605 (2009).

Hyypä, J., Hyypä, H., Leckie, D., Gougeon, F., Yu, X., Maltamo, M., 2008. Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *International Journal of Remote Sensing*, 29(5), 1339-1366.

Jaakkola, A.; Hyypä, J.; Kukko, A.; Yu, X.; Kaartinen, H.; Lehtomäki, M. and Lin, Y., 2010. A low-cost multi-sensoral mobile mapping system and its feasibility for tree measurements. *ISPRS J. Photogram. Remote Sens.* 65, 514–522.

- Järnstedt, J., Pekkarinen, A., Tuominen, S., Ginzler, C., Holopainen, M. and Viitala, R., 2012. Forest variable estimation using a high-resolution digital surface model. *ISPRS Journal of Photogrammetry and Remote Sensing*, 74, 78-84.
- Kankare, V., Vastaranta, M., Holopainen, M., Rätty, M., Yu, X., Hyypä, J., ... and Viitala, R., 2013. Retrieval of forest aboveground biomass and stem volume with airborne scanning LiDAR. *Remote Sensing*, 5(5), 2257-2274.
- Kelcey, J. and Lucieer, A., "Sensor Correction of a 6-Band Multispectral Imaging Sensor for UAV Remote Sensing", *Remote Sensing*, 4, 1462-1493 (2012).
- Krärup, T., Juhl, J. and Kubik, K.. In Götterdammerung over least squares adjustment, *XIV Congress of International Society of Photogrammetry, Hamburg; Hamburg, 1980; pp. 369-378 (1980)*.
- Kraus, K. Photogrammetry, 2007. Geometry from images and laser scans. *Walter de Gruyter*.
- Kurtural, K. & O'Daniel, B. (2007). Crop Estimation in Vineyards. *UK Cooperative Extension Service, University of Kentucky- College of Agriculture*.
- Lange, B., Chang, C., Suma, E., Newman, B., Rizzo, A. S., & Bolas, M. (2011). Development and evaluation of low cost game-based balance rehabilitation tool using the microsoftkinect sensor. *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*, pp. 1831-1834.
- Lass, L. W. and Callihan, R. H., "The effect of phenological stage on detectability of yellow hawkweed (*Hieracium pratense*) and oxeye daisy (*Chrysanthemum leucanthemum*) with remote multispectral digital imagery," *Weed Technology* 11(2), 248-256 (1997).
- Lowe, D.G., 2004. Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*, 60, 91-110.
- Lumme, J., Karjalainen, M., Kaartinen, H., Kukko, A., Hyypä, J., Hyypä, H., et al. (2008). Terrestrial laser scanning of agricultural crops. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37, 563-566.

Mallet, C., & Bretar, F. (2009). Full-waveform topographic lidar: State-of-the-art. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64(1), 1-16.

Martin, S., Dunstone, R., & Dunn, G. (2003). How to Forecast Wine Grape Deliveries Using Grape Forecaster Excel Workbook Version 7; *GWRDC: Adelaide, Australia*; p. 100.

Navarro-Cerrillo, R. M., del Campo, A. D., Ceacero, C. J., Quero, J. L., & Hermoso de Mena, J. (2014). On the importance of topography, site quality, stock quality and planting date in a semiarid plantation: Feasibility of using low-density LiDAR. *Ecological Engineering*, 67, 25-38.

Nuske, S., Achar, S., Bates, T., Narasimhan, S., & Singh, S. (2011). Yield estimation in vineyards by visual grape detection. *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*, pp. 2352-2358.

Lisein, J.; Pierrot, M., Bonnet, S. and Lejeune, P., 2013. A Photogrammetric Workflow for the Creation of a Forest Canopy Height Model from Small Unmanned Aerial System Imagery. *Forests*, 4(4), 922-944.

O'Rourke, J. (1994). Computational geometry in C. *Press Syndicate of the University of Cambridge*, 118.

Pierrot-Deseilligny, M.; Clery, I., 2011. An open source bundle adjustment software for automatic calibration and orientation of set of images. *In Apero, ISPRS Symposium, 3DARCH11, Trento, Italy, March 2-4; pp. 269-276.*

Pope, A. J. (1976). The statistics of residuals and the detection of outliers.

Quan, L. (2010). *Image-based modeling*. New York: Springer.

Richardson, J. J., Moskal, L. M., 2011. Strengths and limitations of assessing forest density and spatial configuration with aerial LiDAR. *Remote Sensing of Environment*, 115(10), 2640-2651.

Schmidt, K. S. and Skidmore, A. K., "Spectral discrimination of vegetation types in a coastal wetland", *Remote Sensing of Environment* 85(1), 92-108 (2003).

Serrano, L., González-Flor, C., & Gorchs, G. (2012). Assessment of grape yield and composition using the reflectance based water index in Mediterranean rainfed vineyards. *Remote Sensing of Environment*, 118, 249-258.

Sethian, J. A. (1999). Level set methods and fast marching methods: evolving interfaces in computational geometry, fluid mechanics, computer vision, and materials science (Vol. 3). *Cambridge university press*.

St-Onge, B., Vega, C., Fournier, R. A., Hu, Y., 2008. Mapping canopy height using a combination of digital stereo-photogrammetry and lidar. *International Journal of Remote Sensing*, 29(11), 3343-3364.

Tao, W.; Lei, Y. and Mooney, P., 2011. Dense Point Cloud Extraction from UAV Captured Images in Forest Area. *Proceedings of the 2011 IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services (ICSDM)*, pp. 389–392.

Turner, D., Lucieer, A. and Watson, C., "Development of an Unmanned Aerial Vehicle (UAV) for hyper resolution vineyard mapping based on visible, multispectral, and thermal imagery," *Proceedings of 34th International Symposium on Remote Sensing of Environment*, p. 4 (2011).

Vermote, E. F., Tanre, D., Deuze, J. L., Herman M. and Morcette, J. J., "Second Simulation of the Satellite Signal in the Solar Spectrum, 6S: an overview," *IEEE Transactions on Geoscience and Remote Sensing* 35(3), 675-686 (1997).

Wallace, L.; Lucieer, A.; Watson, C. and Turner, D., 2012. Development of a UAV-LiDAR system with application to forest inventory. *Remote Sensing*, 4, 1519–1543.

Wang, Z., Boesch, R., & Ginzler, C. (2007). Color and lidar data fusion: application to automatic forest boundary delineation in aerial images. *International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences*.

- Weinacker, H., Koch, B., Heyder, U., & Weinacker, R. (2004). Development of filtering, segmentation and modelling modules for lidar and multispectral data as a fundament of an automatic forest inventory system. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(Part 8), 50-55.
- White, J. C., Wulder, M. A., Varhola, A., Vastaranta, M., Coops, N. C., Cook, B. D., ... and Woods, M., 2013a. A best practices guide for generating forest inventory attributes from airborne laser scanning data using an area-based approach. *The Forestry Chronicle*, 89(6), 722-723.
- White, J. C., Wulder, M. A., Vastaranta, M., Coops, N. C., Pitt, D. and Woods, M., 2013b. The utility of image-based point clouds for forest inventory: A comparison with airborne laser scanning. *Forests*, 4(3), 518-536.
- Wolpert, J., & Vilas, E. (1992). Estimating vineyard yields: Introduction to a simple, two-step method. *American Journal of Enology and Viticulture*, 43(4), 384-388.
- Wulder, M. A., Coops, N. C., Hudak, A. T., Morsdorf, F., Nelson, R., Newnham, G., & Vastaranta, M. (2013). Status and prospects for LiDAR remote sensing of forested ecosystems. *Canadian Journal of Remote Sensing*, 39 (sup1), S1-S5.
- Wulder, M. A., White, J. C., Nelson, R. F., Næsset, E., Ørka, H. O., Coops, N. C., ... and Gobakken, T., 2012. Lidar sampling for large-area forest characterization: A review. *Remote Sensing of Environment*, 121, 196-209.
- Xiang, H. and Tian, L., "Autonomous aerial image georeferencing for an UAV-based data collection platform using integrated navigation system," *ASABE Annual Meeting, Minneapolis, Minnesota (2007)*
- Zarco-Tejada, P. J., Miller, J., Morales, A., Berjón, A., and Agüera, J., "Hyperspectral indices and model simulation for chlorophyll estimation in open-canopy tree crops", *Remote Sensing of Environment*, 90(4), 463-476 (2004).
- Zhang, C. and Kovacs, J., "The application of small unmanned aerial systems for precision agriculture: a review," *Precision Agric* 13(6), 693-712 (2012).

Zhao, W. T. and Peng, J. Y., "VORONOI Diagram-based Path Planning for UAVs," *Journal of System Simulation* 18(2), 159-162 (2006).

ANEXO I

PUBLICACIONES DE CONGRESO, ISPRS *2015*

ANEXO I. PUBLICACIONES DE CONGRESO, ISPRS 2015

- Herrero-Huerta, Mónica and Lindenbergh, R. C. “Automatic Tree Breast Height Diameter Estimation from Laser Mobile Mapping Data in an Urban Context”. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-3/W3, 2015. ISPRS Geospatial Week 2015, La Grande Motte, France, 28 September-3 October 2015*. ISPRS.
- Lindenbergh, R. C., Berthold, D., Sirmacek, B., Herrero-Huerta, M., Wang, J., & Ebersbach, D. “Automated large scale parameter extraction of road-side trees sampled by a laser mobile mapping system”. In *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-3/W3, 2015. ISPRS Geospatial Week 2015, La Grande Motte, France, 28 September-3 October 2015*. ISPRS.

Automatic Tree Breast Height Diameter Estimation from Laser Mobile Mapping Data in an Urban Context

Mónica Herrero-Huerta¹ and Roderik Lindenbergh²

¹*Department of Cartographic and Land Engineering, University of Salamanca, Higher Polytechnic School of Avila, Hornos Caleros 50, 05003, Avila, Spain. Phone number: 0034-920353500-3820, monicaherrero@usal.es*

²*Department of Geoscience and Remote Sensing, Delft University of Technology, 2628 CN Delft, The Netherlands.*

Highlights: This study focuses on developing an innovative methodology to automatically estimate the diameter at breast height (DBH) of urban trees sampled by a Laser Mobile Mapping System (LMMS). The high-quality results confirm the feasibility of the proposed methodology, providing scalability to a comprehensive analysis of urban trees.

Keywords: *breast height diameter, LiDAR, urban trees, laser mobile mapping system, estimation.*

Introduction

Accurate measures of structural parameters of urban trees and monitoring their changes over time are essential to inventory of urban trees and growth models, modelling of carbon cycle and management systems of urban trees [1]. The estimation of these variables has traditionally been done with field inventories via pilot samplings. The advent of recent remote sensing technologies has opened up a new field of possibilities for carrying out such work through non-destructive methods, providing advantages regarding the economic costs involved, the time invested and estimation errors.

Among the various urban tree measurements, DBH (stem diameter at 1.3 m height) is an important tree inventory attribute because it serves as a fundamental parameter in tree allometry and estimation of basal area, thus providing valuable information about individual trees and tree stand structure. Many countries store the DBH of urban trees in cadaster databases for monitoring purposes.

The application of LMMS (Laser Mobile Mapping System) enables to fast and accurately capture 3D data of individual urban trees along the road. However, no research has been done on retrieving DBH using this technology. LMMS operates at the suitable work scale between manual and airborne LiDAR measurements. The latter fails to capture the complete vertical distribution of the canopy [2]. Terrestrial Laser Scanning has been used for estimating tree parameters[3], but being time-consuming compared with LMMS in an urban context. However, the method proposed has to face additional difficulties due to the specific acquisition geometry of the technology mentioned, such as the partial 3D data (only one side view), or having to deal with occluding vegetation, leading to underestimations compared to manually collected field data [4].

The aim of the present work is to develop an efficient and precise methodology in a novel way, to obtain DBH of urban trees destined for inventories based on point clouds coming from LMMS. Additionally, the influence of the density of points on the accuracy of deriving DBH estimations were investigated.

Materials and Methods

Laser Mobile Mapping System

For this work, data acquired by Fugro Drivemap is considered. This LMMS is composed of two high performance laser scanners type Riegl VQ250, a four-wheeled all-terrain vehicle and a navigation unit. The Global Positioning System has 10 Hz of positioning rate and the laser pulse rate is 1.333·10⁶ pulses/s, being the maximum density 115000 points/m², the field of view 360°x 26.8°, the ranging accuracy less than 2cm and the maximum range 30 m.

Ground Inventory Data

The ground truth of the DBH was established using a measurement tape by a qualified operator at 5 centimeter precision. It should be remarked that the studied trees are less than 10 meters from the road.

DBH tree extraction Methodology

Before estimating the DBH, the extraction of individual trees of the point cloud is necessary through an automated workflow by voxel analysis (not the aim of this study). For the DBH tree extraction methodology the following steps are performed for each tree (Figure 1):

1). Outliers removal.

A statistical analysis on each point's neighbourhood is performed by assuming a Gaussian distribution. All points whose mean distance is outside an interval defined by the global mean distance and standard deviation are considered as outliers and removed from the dataset.

2). Extraction of trunk data.

The limit between the trunk and canopy is calculated by the curvature change of the histogram that represents the number of filled voxels of 0.25 cm^3 size as a function of height.

If the histogram shows there are ramifications in the trunk, k-means is used to assign a cluster (k clusters) to each data point ($\mathbf{x}_i, i=1 \dots n$). K-means is a clustering method that aims to find the positions $\mu_i, i=1 \dots k$ of the clusters that minimize the Euclidean distance from the data points to the cluster (Equation 1):

$$\arg \min_c \sum_{i=1}^k \sum_{x \in c_i} d(x, \mu_i) = \arg \min_c \sum_{i=1}^k \sum_{x \in c_i} ||x - \mu_i||_2^2 \quad (1)$$

where c_i is the set of points that belong to cluster i .

3). Determining the orientation of each trunk by Principal Component Analysis (PCA) and projecting the trunk points into a plane orthogonal to the axis corresponding to the principal direction.

A classical approach consists in performing a PCA of the 3D coordinates of the point cloud of the trunk. This statistical analysis uses the first and second moments of the point cloud, and results in three orthogonal vectors centered on the centroid of the point cloud. The PCA synthesizes the distribution of points along the three dimensions, and thus models the principal directions and magnitudes of variation of the point distribution around the center of gravity [6].

4). Fitting a circle to the projected trunk points by using RANSAC (RANdom Sample Consensus) to mitigate the influence of outliers [7].

DBH was retrieved from laser datasets by circle fitting at different height bins. This can be done because of the assumption that the diameter is not significantly varying along a short length of the stem for mature trees.

Points that deviated most from a fitted circle were considered noise and removed for DBH estimations through the RANSAC method.

5). Quality control by obtaining the RMSE of the DBH estimated and measured at different height bin sizes.

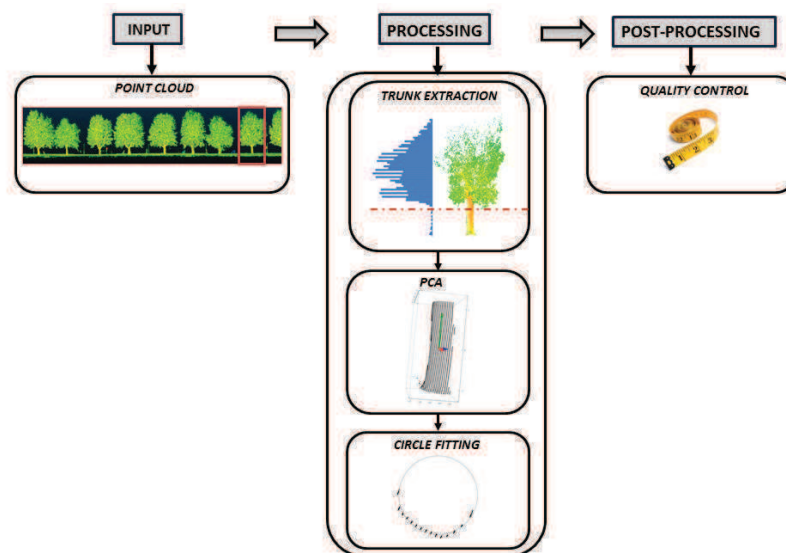


Figure 1. Workflow of the DBH Methodology

Experimental Results

The study area is located at the Delft University of Technology campus (lat. $52^{\circ}00' \text{ N}$; long. $4^{\circ}22' \text{ E}$; 1 m asl, The Netherlands) and tree species include *Plantanus* and *Quercus*. Data collection was performed on the 4th of November 2014 covering an area of approximately $750 \times 1200 \text{ m}$ on a day without wind. The dataset consists of 53,958,666 points, with the x , y and z coordinates and intensity. A pre-processing step of this dataset was carried

out in order to obtain the individual trees of the zone of interest. After that, the point cloud has 1,860,156 points with no intensity. There are 29 trees in total, 14 *Platanus* and 15 *Quercus*. The diameters of the first one are bigger than the others.

The accuracy of DBH estimation is influenced by several factors. Different height bins for determining the number of points to fit the circle, were tested to derive reliably DBH estimations. In addition, DBH estimation errors were confronted with the number of points to fit the circle but a relation was not seen.

Table 1 collects the robust statistical parameters of the linear regression established between the actual and the estimated DBH at different height bin sizes. The probability of success to achieve a right DBH defined by this parameters, is also included. From this analysis, it is possible to conclude that 20 cm height bin provides better results, from 1.20 m to 1.40 m height of each individual tree.

Table 1. Correlation coefficients and probability of success at different bin sizes

Circle Fitting Height Bin (m)	R ²	RMSE (cm)	Probability of Success (%)
1,25-1,35	0,792	5,67	62,1
1,20-1,40	0,837	4,35	79,3
1,10-1,50	0,688	6,45	75,9
1,00-1,60	0,600	12,12	86,2

Conclusions

This research presents a non-invasive method with application to urban tree inventory that consists of DBH estimation. The method is fast, reliable, robust and objective, and could serve to take decisions in advance regarding actions to be taken in urban trees and planning the management and maintenance optimally. This study also discussed the influence of the number of points to fit the circle and circle fitting height bin size on the influence of DBH estimation accuracy, validated against field measurements. Regarding these variables, the results show that there is no significant relation between the number of points and the DBH estimation errors. A 20 cm height bin provides better results, reaching a R² value of 0.84 and a RMSE of 4.35 cm with a probability of success of 79.3%. In addition, the results show that working only on one side of the tree, the visible side from the road, is still feasible for approximating the DBH with an accurate and precise fit.

This methodology can be extrapolated to a comprehensive study of urban trees.

It should be mentioned that the proposed methodology is part of a robust and efficient workflow which considers the automated, large scale extraction of tree sizes and locations sampled by a laser mobile mapping system. It includes tree location, level height and crown width throw a sensitivity analysis.

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References

- [1] Næsset, Erik. "Practical large-scale forest stand inventory using a small-footprint airborne scanning laser." *Scandinavian Journal of Forest Research* 19.2 (2004): 164-179.
- [2] Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in physical geography*, 27(1), 88-106.
- [3] Srinivasan, Shruthi, et al. "Terrestrial Laser Scanning as an Effective Tool to Retrieve Tree Level Height, Crown Width, and Stem Diameter." *Remote Sensing* 7.2 (2015): 1877-1896.
- [4] Moskal, L. M., & Zheng, G. (2011). Retrieving forest inventory variables with terrestrial laser scanning (TLS) in urban heterogeneous forest. *Remote Sensing*, 4(1), 1-20.
- [5] Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. *Applied statistics*, 100-108.
- [6] Van Goor, B., Lindenbergh, R. C., & Soudarissanane, S. S. (2011, August). Identifying corresponding segments from repeated scan data. In *ISPRS Workshop Laser Scanning 2011*, Calgary, Canada, 29-31 August 2011; IAPRS, XXXVIII (5/W12), 2011. International Society for Photogrammetry and Remote Sensing (ISPRS).
- [7] Schnabel, Ruwen, Roland Wahl, and Reinhard Klein. "Efficient RANSAC for Point Cloud Shape Detection." *Computer graphics forum*. Vol. 26. No. 2. Blackwell Publishing Ltd, 2007.

AUTOMATED LARGE SCALE PARAMETER EXTRACTION OF ROAD-SIDE TREES SAMPLED BY A LASER MOBILE MAPPING SYSTEM

R.C. Lindenbergh^{a,*}, D. Berthold^b, B. Sirmacek^a, M. Herrero-Huerta^a, J. Wang^a, D. Ebersbach^b

^a Dept. of Geoscience & Remote Sensing, Delft University of Technology, Delft, The Netherlands
(r.c.lindenbergh, b.sirmacek, m.herrerohuerta, jinhu.wang)@tudelft.nl

^b LEHMANN + PARTNER GmbH, Schwerborner Straße 1, D-99086 Erfurt - (Berthold,Ebersbach)@lehmann-partner.de

Commission III, WG III/5

KEY WORDS: big data, laser mobile mapping, tree parameters, urban, voxels

ABSTRACT:

In urbanized Western Europe trees are considered an important component of the built-up environment. This also means that there is an increasing demand for tree inventories. Laser mobile mapping systems provide an efficient and accurate way to sample the 3D road surrounding including notable roadside trees. Indeed, at, say, 50 km/h such systems collect point clouds consisting of half a million points per 100m. Method exists that extract tree parameters from relatively small patches of such data, but a remaining challenge is to operationally extract roadside tree parameters at regional level. For this purpose a workflow is presented as follows: The input point clouds are consecutively downsampled, retilled, classified, segmented into individual trees and upsampled to enable automated extraction of tree location, tree height, canopy diameter and trunk diameter at breast height (DBH). The workflow is implemented to work on a laser mobile mapping data set sampling 100 km of road in Sachsen, Germany and is tested on a stretch of road of 7km long. Along this road, the method detected 315 trees that were considered well detected and 56 clusters of tree points where no individual trees could be identified. Using voxels, the data volume could be reduced by about 97 % in a default scenario. Processing the results of this scenario took ~2500 seconds, corresponding to about 10 km/h, which is getting close to but is still below the acquisition rate which is estimated at 50 km/h.

1. INTRODUCTION

Recent years saw a rapid development of sensor systems that efficiently sample our 3D environment at high detail, (Vosselman and Maas, 2010). Mobile mapping systems implemented in helicopters and cars obtain point clouds consisting of millions to billions of points at a daily basis, (Haala et al., 2008, Puente et al., 2013). In addition, methods from e.g. computer vision and computational geometry became available over the last years that are able to extract useful information from such 3D point clouds by estimating locations and sizes of the different objects sampled by the point clouds, (Puttonen et al., 2011, Rutzinger et al., 2010). Such methods are typically demonstrated in the scientific community at case study scale however. Examples are given of the extraction of geometric parameters from one facade, one or a few trees or 300 m of road furniture, (Monnier et al., 2012). So far, the number of publications that specifically addresses the difficulties of processing large urban point clouds is limited, (Weinmann et al., 2015).

Unfortunately it turns out far from trivial to efficiently exploit the possibilities of combining large 3D point clouds and 3D geometry extraction methods, (Krämer and Senner, 2015). Computers have limited memory capacity, which means that input data needs to be (re)divided into manageable chunks. At the same time an automated division strategy will often affect the objects of interest, as data division will take place before object extraction. Another problem is that the results of geometry extraction algorithms often depend on parameters. For an individual case study such parameters can easily be tuned. When automatically processing an unseen, large data set with a variety of different realizations of the same object type, parameter tuning should be either unnecessary or automated. Another challenge is to make algorithms responsi-

ble for the compatibility between consecutive steps: the output of step $(k - 1)$ is the input of step k . Even powerful geometry extraction methods may fail when sampling is locally hampered by unfavorable acquisition conditions. Therefore it is important that a human operator responsible for quality control is automatically guided to such locations.

For the workflow presented in this paper the strategy to mitigate the negative effects of large point clouds on computational feasibility, is to process as much as possible at voxel level, rather than at the individual point level. That is, the original point cloud is subdivided into small cubic cells, the voxels, and consecutive information extraction takes place by analyzing local voxel configurations. Switching to voxels has some advantages. Data volume and therefore memory usage is reduced, as many points in one voxel are simply replaced by one single voxel value (Either voxel center, or center of gravity of the points in the voxel); The effect of varying point densities in scan data is largely resolved and irregular points are replaced by regular voxels cells, which makes spatial indexing more efficient; Smaller gaps in data coverage caused by occlusions in the scanning play a smaller role because of the lower resolution of the voxels. Voxels are the most simple way to subdivide a 3D domain. More sophisticated and more scalable is to organize a point cloud in a so-called kd-tree, which allows to prune the point cloud to a certain level, (Triebl et al., 2006), or in an octree.

Even when voxels are processed instead of the original points, files consisting of these voxels can grow arbitrary large if simply merged without strategy. Therefore some additional tiling and stitching strategy is needed that chops data in manageable chunks, either for single node processing or for parallel execution, (Yang and Zhang, 2015). If one such chunk can be processed in a reasonable time, the method would not change if you process 1km, 10km, or 10 000 km of data along urban streets, which is

*Corresponding author

exactly what is required in practical applications. Here ‘reasonable time’ is often defined such that processing the data does not take more time than acquiring the data. So, the only remaining requirement is that it should be demonstrated that processing a chunk doesn’t take more time than acquiring it.

The above mentioned advantages of using voxels, kd-trees and octrees are reasons that several voxel based methods have been designed for natural tree related processing of point clouds. (Popescu and Zhao, 2008) divide their airborne point clouds of trees in voxels to determine the transition between trunk and canopy. (Bucksch et al., 2010) organize notably panoramic scanner point clouds sampling trees in voxels to reconstruct the branch structure of trees; (Wu et al., 2013) organize laser mobile mapping data in voxels to divide tree points over individual trees. (Cabo et al., 2014) detect pole like objects in mobile mapping scan points using voxels, which allowed to work on 20-30 % of the original data volume. (Lim and Suter, 2009) use initial individual point features to group points in so-called super voxels, which are used in consecutively obtaining point cloud classification results of a panoramic scanner point cloud.

This short literature review indicates that in principle methods exist that satisfy the needs of the workflow presented in this paper. Still it was chosen to use methods that were implemented from scratch for the following reasons. Available methods typically solve a problem at hand in an approximate way, in the sense that they may estimate related parameters, but not exactly the parameters required by a particular application. In addition, available methods were often developed while solving a problem within the particular context of a specific data set. Applying the method on different data often gives incorrect results. Note that this problem is partly solved by data processing contests, e.g. (Vallet et al., 2015), which compare methods in a more uniform way. Another issue is that within a workflow back-to-back processing is required: the output of the previous module is the input of the next module. A condition which is typically not fulfilled without extra work when relying on available methods. Finally that a method is published doesn’t mean that an implementation is available, nor that input and output formats, programming language and targeted operating system match. For the combination of these reasons it was decided to implement the workflow from scratch using relatively light but flexible methodology.

2. METHODOLOGY

In this work we will present a processing chain aiming at the robust and efficient large scale extraction of tree sizes and locations.

2.1 Data description

The processing chain is initially tested on 7 km of laser mobile mapping data, sampling a test route in Saxony, Germany. The laser mobile mapping system contains a clearance profile scanner from Fraunhofer IPM, collecting up to 2 million points per second. The relative precision of each single laser point is 4 mm. The absolute geographic precision of the point cloud is about 15 cm, ensured by a 2 antenna GPS/GNSS positioning system supported by a 200 Hz IMU from APPLANIX and differential GPS corrections applied in postprocessing.

The mobile mapping system originally records the laser scanner data on the road in a binary format until 1 GByte is reached per file (and then the next 1 GB container will be filled etc.). These binary data containers were converted to xyz-format and separated into 10 meter chunks. These 10 meter chunks are the starting point of the processing chain described in this work. The test

road is represented by 830 xyz files (the 10 meter chunks) of in total 17 GByte. In single cases, the car had to stop because of traffic which lead to larger files. Together, these 830 files contain 427 186 054 points. The processing chain below doesn’t use the intensity data, only the xyz information. In its final form the processing chain will be used to extract tree locations and sizes for 100 km of laser mobile mapping data. For this area, ground truth tree locations obtained by a human operator are available.

2.2 Processing chain

The processing chain consist of the steps listed below. Each step corresponds to an algorithm which allows the user to specify up to two parameters as indicated. Some more details are given below.

Downsampling and retiling, with two parameters: voxel size, and maximum number of points per tile.

Tree point classification, with two parameters: grid size and minimum tree height:

Tree segmentation, with two parameters, minimum canopy diameter and voxel size

Tree parameters, rough, no parameters

Upsampling per tree, no parameters

Tree parameters, fine, no parameters

What follows is a short description of the described methodology.

The input data is provided in chunks that in principal correspond to 10m of road. It is assumed that these chunks are ordered according to the order in which they were sampled. A main step to make the processing feasible is actually the first step, the downsampling and retiling step. In this step, input data chunks are read and uniformly downsampled. This means that a fixed voxel size is set by the user, e.g. 30 cm, which defines a 3D grid over the scene sampled by the chunk. Consecutively all original points in a given voxel cell are replaced by the center of gravity of those points. Downsampled points are collected in order until a preset number of points is reached. These, for example 200 000 points are written to a file. Therefore this step will result in files containing at most 200 000 points at a resolution of 30 cm.

These retiled files are the input for the classification step, (Sirmacek and Lindenbergh, 2015). The aim of this step is to divide the 3D points in two classes, tree and non-tree points. In this step a 2D grid is defined over the data of a given grid size, e.g. 20 cm. For each grid cell, the number of 3D points are counted whose xy location belong to the grid cell. Local maxima in the resulting counts are assumed to correspond to tree locations. 3D points above the ground and close to these tree locations will be assigned to the tree class, the other points to the non-tree class. To distinguish trees from shrubs, a minimal tree height can be defined by the user, for example 2 m. A disadvantage of the current algorithm is that it sometimes generates false positives at street poles. This step is also illustrated in Figure 1. In the left image, points colored gray are non-tree points, while the dark green points are classified as trees.

The classified points proceed to the tree segmentation step. Goal of this step is to segment the tree points into individual trees. To do so, tree points are again distributed over a 3D voxel structure. First local maxima are detected. If a local maximum is sufficiently prominent, according to the minimum canopy width

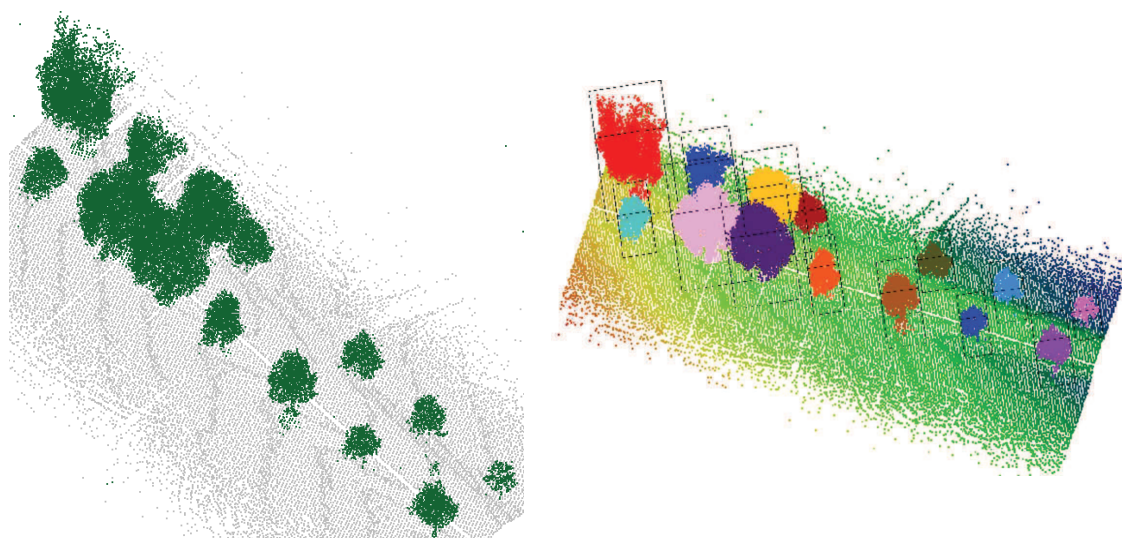


Figure 1: **Left** Points classified as trees (green points) and other (gray points). **Right** Identified individual trees (solid colors) in their bounding box.

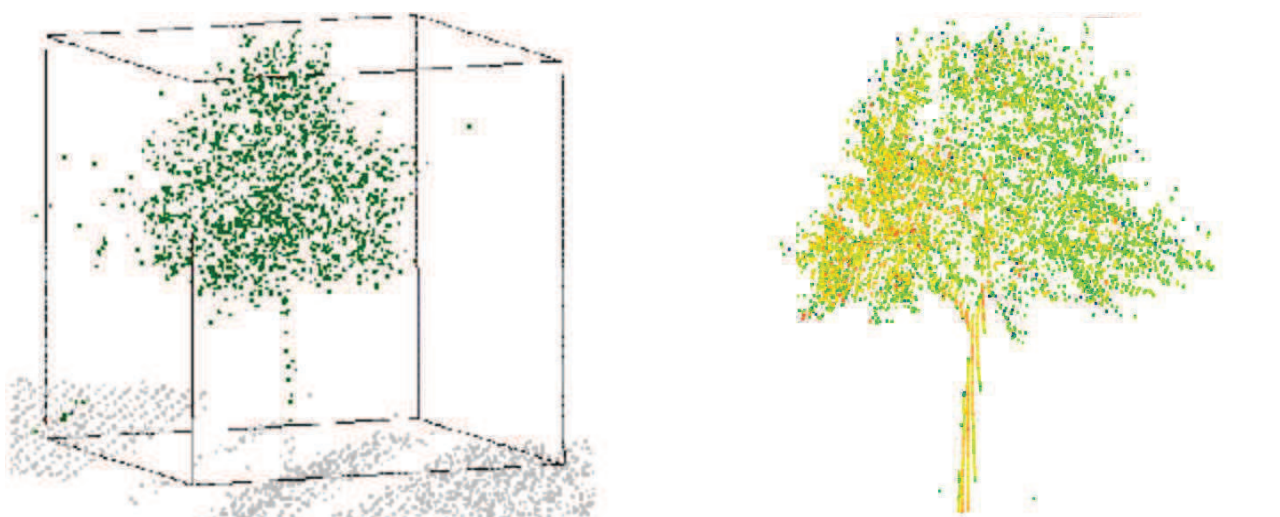


Figure 2: Restoring of the original tree points for one individual tree. **Left.** Voxelized points belonging to a tree (in dark green) and not belonging to this tree (in gray). **Right.** Using the bounding box in the left image, the original points are restored in the right image. These original points are used to determine final tree parameters like Diameter at Breast Height (DBH).

parameter, it is selected as a seed point for growing a tree by traversing the layers of the adjacent octree cells from top to bottom. Voxel cells at a certain layer in between two seed points, are assigned to one of the two seed points according to a proximity criterion. The success of this tree segmentation step is indicated by a quality flag which can be used to guide a human operator to situations where automated processing was not successful.

As a result of the tree segmentation step, tree voxels are assigned to individual trees. By determining the bounding box of all voxels belonging to one tree, a first estimation of the canopy width, tree height and tree location is obtained. Indeed, the canopy width and tree height are simply the width and height of the bounding box, while an estimation for the tree location is the intersection of the horizontal diagonals of the bounding box. This step is illustrated on the right in Figure 1. Different trees have different colors, and around each tree a bounding box is visible.

Note that all of the tree extraction steps above were performed on the uniform downsampled point cloud of, say, 30 cm resolution. As by now individual trees have been identified, it is possible and also computationally feasible to go back to the full resolution original point cloud, as the correspondences between downsampled points and original points were maintained.

The final step is therefore performed per individual tree on the original points, compare Figure 2. In the left image, the downsampled points are shown, in the right image, the original points are restored. The number of downsampled tree points in this example is 1702, while the original number of points inside the bounding box is 22 283. Using a histogram analysis of the vertical distribution of the tree points, compare also (Popescu and Zhao, 2008), the trunk is separated from the canopy. The direction of the trunk is estimated by Principal Component Analysis (PCA) and the diameter at breast height (DBH), which is the diameter of a tree at 1m30, (Bucksch et al., 2014), is estimated by determining the diameter of a circle through tree points, after

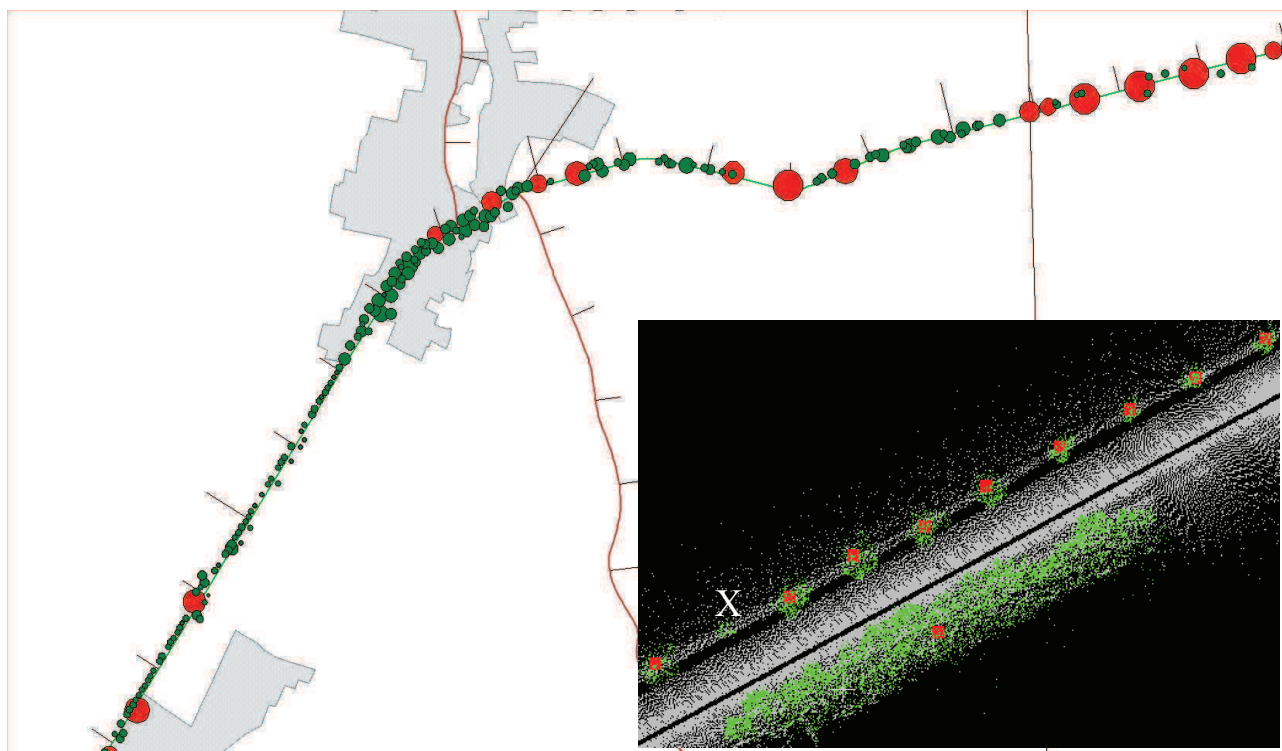


Figure 3: **Large figure:** Identified trees. Green circles correspond to tree locations marked by the method as correct, red circles correspond to tree points where the algorithm was not able to identify individual trees. **Small figure:** some tree classification and segmentation results. Green points were identified as tree points. The red markers indicate single trees (top of the road) or a cluster of trees that couldn't be segmented (bottom of the road).



Figure 4: An estimation of the Diameter at Breast Height (DBH) is obtained by fitting a circle to projected trunk points of an appropriate portion of the trunk.

removing outliers using RANSAC, (Fischler and Bolles, 1981), compare also Figure 4. The figure shows only a partially sampled circle, which corresponds to the mobile mapping system seeing only the part of the trunk that is facing the road. The PCA step in combination with restoring the original point cloud can also be used to improve the estimation of the location of the tree by determining the intersection of the principal axis with the terrain.

2.3 Sensitivity analysis

There is an apparent tradeoff between the different parameters. Downsampling with a smaller voxel size in the first step will result in a higher resolution downsampled file, which contains more details, from which consecutive steps could profit. At the same time, if the maximum number of points per tile is kept fixed, the spatial extent of the tile will shrink. This implies that more trees will be cut in two at tile boundaries, which will negatively affect

the results.

Increasing the number of points per tile will in turn have a negative effect on the computational performance of the processing chain. In addition, the first three steps, downsampling, classification and tree segmentation, all use a 2D or 3D grid. How the sizes of these grids interact should be further investigated.

Note that in the current workflow the first three steps all use voxels or pixels. In the current implementation the different voxel and pixel sizes are not yet aligned. Therefore it is for example possible that when using a voxel size of 30 cm in the first step, as stated as an example above, and having a grid size of 20 cm in the second step, some grid cells are in fact empty. It would be preferably if these sizes were aligned, as it would further simplify the tuning of the remaining parameters and the interpretation of unexpected results.

3. RESULTS

All above mentioned steps have been implemented, but the final tree parameter estimation step could not yet been tested within the workflow.

As 'default' settings, the values as shown in Table are used. The large image in Figure 3 shows results for part of the 7km of road considered as case study. Green disks indicate trees identified by the processing chain. The diameter of each disk corresponds to the estimated width of the tree canopy. Red disks correspond to tree points where the segmentation method was not able to identify single trees. The algorithm indicates this by a quality flag, which guides an operator to these cases. Again, the diameter of the red disks correspond to the width of the bounding box, in

Step	Parameter	Value
Downsampling	Voxel size	0.3 m
	Max points per tile	20 000
Classification	Grid size	0.2 m
	Min. tree height	2 m
Segmentation	Voxel size	1 m
	Min. canopy diameter 6 m	

Table 1: Default settings workflow

this case of the cluster of tree points that couldn't be segmented. As such cluster in reality typically corresponds to a number of trees, the diameters of the red disks are in general larger than those of the green disks. In total 315 trees were identified using default settings. For an additional 58 tree point clusters the tree segmentation step didn't succeed in identifying individual trees. Note however, that the locations of the identified trees currently have not yet been validated using the ground truth data.

The small image in Figure 3 illustrates some of the intermediate steps. The results of the classification are indicated in green (tree points) and grey (non tree points). Locations of successfully identified trees at the top of the road are indicated by a red marker. Note that a small tree marked 'X' was not identified, probably because it was too small and therefore removed. The tree segmentation method failed on the large cluster of tree points at the bottom of the road. In this case, the location of the cluster is still reported, but with a quality flag indicating the lack of success. In this case also a human operator would probably have difficulties to separate this cluster into individual trees.

The effect of using voxels on the data volume is shown by the following example. Retiling the first 50 tiles using a voxel size of 30 cm reduced the number of points from 23 282 574 to 518 365 points, which corresponds to a reduction in data volume of 97.8 %.

Increasing the tile size could affect memory usage in a negative way but should decrease tiling effects. The effect of changing the voxel size in the first step is less obvious, as also consecutive steps use voxels. Full evaluation of results of different scenarios, including validation against ground truth, will take place after the voxel sizes have been harmonized throughout the workflow

The tests in Table 1 were run on a desktop PC with Intel Xeon 3.6GHz processor and 16GB of RAM. All algorithms were implemented in C++ and compiled and run on the Ubuntu 14.04 64-bit operating system. Running the scenario with the default settings, corresponding to the first row in Table 1 took 2573 seconds in total, which means that 1 km of data takes about 2573:7 km = 368 seconds. This processing speed corresponds to roughly 10 km an hour. This means that the initial goal of processing at the same rate as the acquisition is close but not yet met, as this probably would mean that the processing rate should be improved by a factor five. Probably this improvement could be reached by a further optimization of the current code.

The total computation time of the presented scenario's is divided over the different steps as follows: Retiling takes approximately 65 %, classification takes 32 % and tree separation 2 %. Change of scenario has no large effect on this division, that is effects are not more than a few per cent. It makes sense that computational efforts drop throughout the workflow. Retiling still considers the full input point clouds and file reading and writing is required. Classification only operates on voxels. Finally, tree separation works on tree voxels only. The final tree parameter estimation step, where the full point clouds within the bounding boxes are restored, were not available for testing yet.

CONCLUSIONS

In paper a processing chain aiming at the extraction of tree locations and tree sizes from laser mobile mapping data is presented. All-though further validation is needed, initial results indicate that the workflow is able to extract individual trees at sufficient quality and at a rate that is approximating the data acquisition rate: processing takes place at a rate of about 10 km/h. For efficient processing, the input is downsampled using voxels to a volume that is below 3 % of the original data volume. Besides validation, still harmonization between the parameters in the different steps is required. Such steps, in combination with code optimization are expected to be sufficient to reach the final goal of automatized estimation of features sampled by mobile mapping at a rate that matches the acquisition speed and at a quality that matches the result of a human operator.

ACKNOWLEDGMENTS

This work is initiated on behalf of the LISt-GmbH, kindly supported by the Saxon State Ministry for Economic Affairs, Labour and Transport, Germany. The research is partly funded by the FP7 project IQmulus (FP7-ICT-2011-318787), aiming at the design and implementation of a high volume fusion and analysis platform for geospatial point clouds, coverages and volumetric data sets.

REFERENCES

- Bucksch, A., Lindenbergh, R., Abd Rahman, M. Z. and Menenti, M., 2014. Breast height diameter estimation from high-density airborne LiDAR data. *IEEE Geoscience and Remote Sensing Letters* 11(6), pp. 1056 – 1060.
- Bucksch, A., Lindenbergh, R. and Menenti, M., 2010. SkelTre – Robust skeleton extraction from imperfect point clouds. *Visual Computer* 26(10), pp. 1283 – 1300.
- Cabo, C., Ordonez, C., García-Cortés, S. and Martínez, J., 2014. An algorithm for automatic detection of pole-like street furniture objects from mobile laser scanner point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing* 87, pp. 47 – 56.
- Fischler, A. and Bolles, C., 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM* 24(6), pp. 381 – 395.
- Haala, N., Peter, M., Kremer, J. and Hunter, G., 2008. Mobile LiDAR mapping for 3D point cloud collection in urban areas – a performance test. *International Archive of Photogrammetry, Remote Sensing and Spatial Information Sciences* 37, pp. 1119 – 1127.
- Krämer, M. and Senner, I., 2015. A modular software architecture for processing of big geospatial data in the cloud. *Computers & Graphics* 49, pp. 69 – 81.
- Lim, E. and Suter, D., 2009. 3D terrestrial LIDAR classifications with super-voxels and multi-scale conditional random fields. *Computer-Aided Design* 41(10), pp. 701–710.
- Monnier, F., Vallet, B. and Soheilian, B., 2012. Trees detection from laser point clouds acquired in dense urban areas by a mobile mapping system., *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 3(3), pp. 245 – 250.
- Popescu, S. C. and Zhao, K., 2008. A voxel-based lidar method for estimating crown base height for deciduous and pine trees. *Remote Sensing of Environment* 112(3), pp. 767 – 781.

Puente, I., Jorge, H. G. ., Martínez-Sánchez, J. and Arias, P., 2013. Review of mobile mapping and surveying technologies. *Measurement* 46(7), pp. 2127 – 2145.

Puttonen, E., Jaakkola, A., Litkey, P. and Hyypä, J., 2011. Tree classification with fused mobile laser scanning and hyperspectral data. *Sensors*, 11(5), pp. 5158-5182. *Sensors* 11(5), pp. 5158 – 5182.

Rutzinger, M., Pratihast, A., Oude Elberink, S. and Vosselman, G., 2010. Detection and modelling of 3d trees from mobile laser scanning data. *ISPRS Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 38(5), pp. 521 – 525.

Sirmacek, B. and Lindenbergh, R., 2015. Automatic classification of trees from laser scanning point clouds. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. II-3/W5.

Triebel, R., Kersting, K. and Burgard, W., 2006. Robust 3D scan point classification using associative markov networks. In: *Proceedings of the 2006 IEEE International Conference on Robotics and Automation*, Orlando, United States.

Vallet, B., Brédif, M., Serna, A., Marcotegui, B. and Paparoditis, N., 2015. Terramobilita/iqmulus urban point cloud analysis benchmark. *Computers & Graphics* 49, pp. 126 – 133.

Vosselman, G. and Maas, H. (eds), 2010. *Airborne and Terrestrial Laser Scanning*. Whittles Publishing.

Weinmann, M., Urban, S., Hinz, S., Jutzi, B. and Mallet, C., 2015. Distinctive 2D and 3D features for automated large-scale scene analysis in urban areas,. *Computers & Graphics* 49, pp. 47– 57.

Wu, B., Yu, B., Yue, W., Shu, S., Tan, W., Hu, C., Huang, Y., Wu, J. and Liu, H., 2013. A voxel-based method for automated identification and morphological parameters estimation of individual street trees from mobile laser scanning data. *Remote Sensing* 5(2), pp. 584–611.

Yang, J. and Zhang, J., 2015. Parallel performance of typical algorithms in remote sensing-based mapping on a multi-core computer. *Photogrammetric Engineering & Remote Sensing* 81, pp. 373 – 385.

ANEXO II

FACTOR DE IMPACTO DE LAS PUBLICACIONES

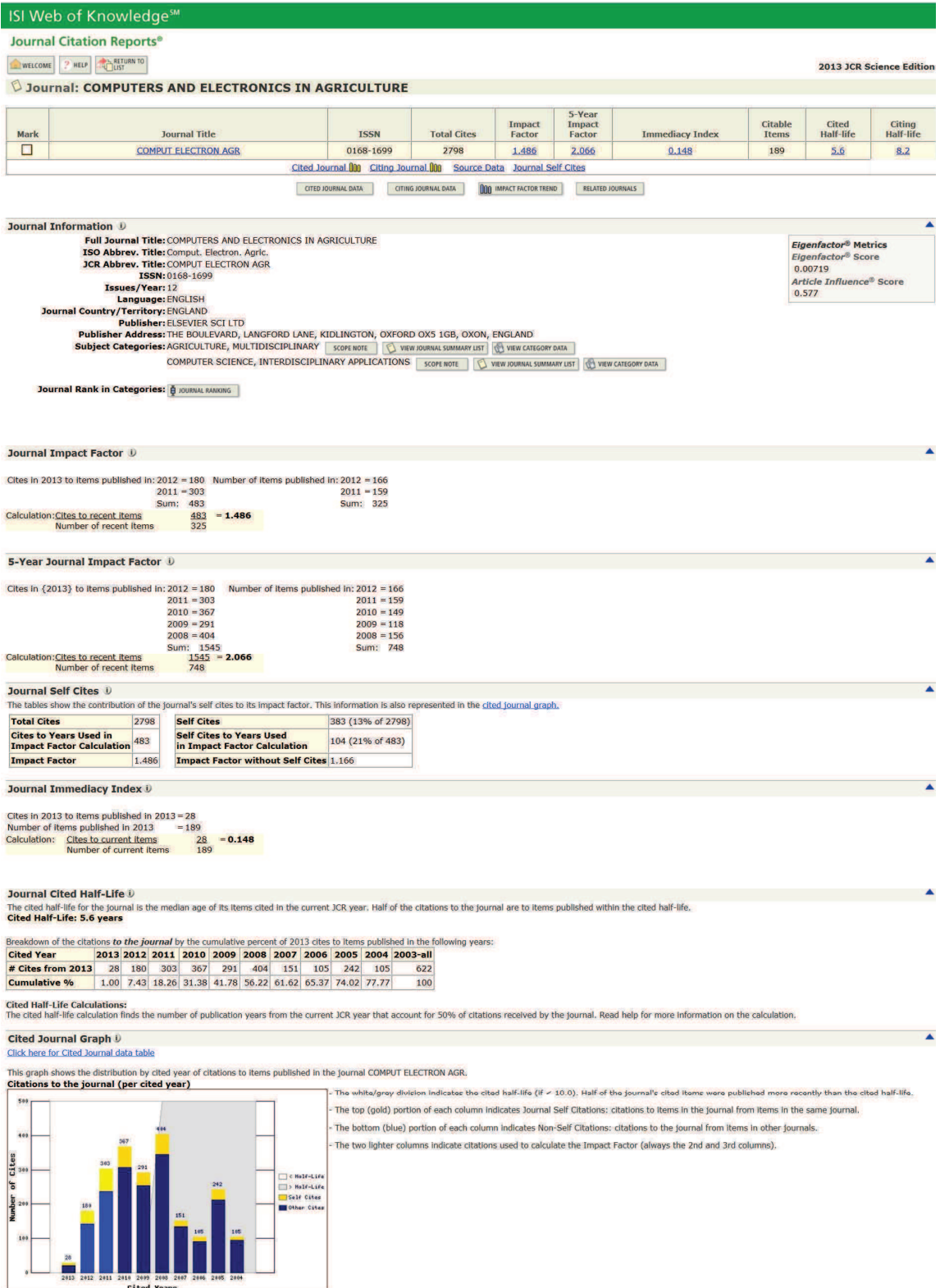
ANEXO II. FACTOR DE IMPACTO DE LAS PUBLICACIONES

1. Vicarious Radiometric Calibration of a Multispectral Sensor from an Aerial Trike Applied to Precision Agriculture

2. Vineyard Yield Estimation by Automatic 3D Bunch Modelling in Field Conditions

Descripción del factor de impacto y documentación de la revista:

Nombre de la revista:	COMPUTERS AND ELECTRONICS IN AGRICULTURE
URL:	http://www.journals.elsevier.com/computers-and-electronics-in-agriculture/
Editorial:	ELSEVIER
ISSN:	0168-1699
Factor de impacto (2013):	1.486
Cuartil:	Q1



Journal Citing Half-Life

The citing half-life for the journal is the median age of the items the journal cited in the current JCR year. Half of the citations in the journal are to items published within the citing half-life.

Citing Half-Life: 8.2 years

Breakdown of the citations *from the journal* by the cumulative percent of 2013 cites to items published in the following years:

Cited Year	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003-all
# Cites from 2013	89	389	553	502	475	461	372	362	337	314	2689
Cumulative %	1.36	7.31	15.76	23.43	30.69	37.73	43.42	48.95	54.10	58.90	100

Citing Half-Life Calculations:

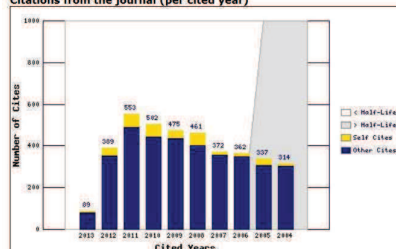
The citing half-life calculation finds the number of publication years from the current JCR year that account for 50% of citations in the journal. Read help for more information on the calculation.

Citing Journal Graph

[Click here for Citing Journal data table](#)

This graph shows the distribution by cited year of citations from current-year items in the journal COMPUT ELECTRON AGR.

Citations from the journal (per cited year)



- The white/grey division indicates the citing half-life (if ≈ 10.6). Half of the citations from the journal's current items are to items published more recently than the citing half-life.
- The top (gold) portion of each column indicates Journal Self-Citations: citations from items in the journal to items in the same journal.
- The bottom (blue) portion of each column indicates Non-Self Citations: citations from the journal to items in other journals.

Journal Source Data

	Citable items			Other items
	Articles	Reviews	Combined	
Number in JCR year 2013 (A)	185	4	189	4
Number of references (B)	6124	415	6539	4.00
Ratio (B/A)	33.1	103.8	34.6	1.0

Journal Ranking

For 2013, the journal **COMPUTERS AND ELECTRONICS IN AGRICULTURE** has an Impact Factor of **1.486**.

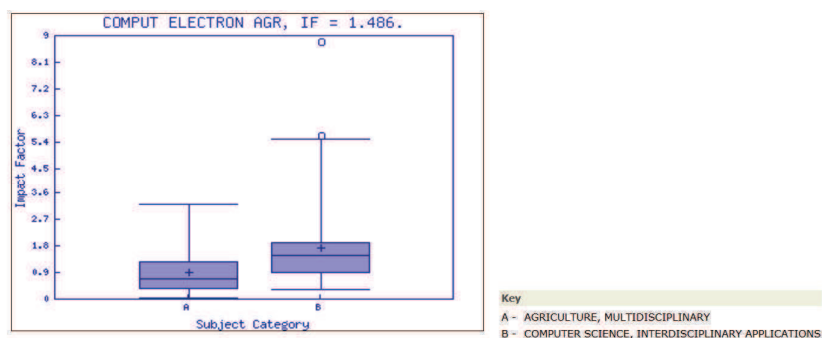
This table shows the ranking of this journal in its subject categories based on Impact Factor.

Category Name	Total Journals in Category	Journal Rank in Category	Quartile in Category
AGRICULTURE, MULTIDISCIPLINARY	56	10	Q1
COMPUTER SCIENCE, INTERDISCIPLINARY APPLICATIONS	102	49	Q2

Category Box Plot

For 2013, the journal **COMPUTERS AND ELECTRONICS IN AGRICULTURE** has an Impact Factor of **1.486**.

This is a box plot of the subject category or categories to which the journal has been assigned. It provides information about the distribution of journals based on Impact Factor values. It shows median, 25th and 75th percentiles, and the extreme values of the distribution.



3. Dense Canopy Height Model from a low-cost photogrammetric platform and LiDAR data

Descripción del factor de impacto y documentación de la revista:

Nombre de la revista:	TREES-STRUCTURE AND FUNCTION
URL:	http://www.editorialmanager.com/tsaf/default.aspx
Editorial:	SPRINGER
ISSN:	0931-1890
Factor de impacto (2014):	1.651
Cuartil:	Q1

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2014 JCR Science Edition

Journal: TREES-STRUCTURE AND FUNCTION

Mark	Journal Title	ISSN	Total Cites	Impact Factor	5-Year Impact Factor	Immediacy Index	Citable Items	Cited Half-life	Citing Half-life
<input type="checkbox"/>	TREES-STRUCT FUNCT	0931-1890	3454	1.651	1.928	0.323	155	8.3	>10.0

[Cited Journal Data](#) [Citing Journal Data](#) [Source Data](#) [Journal Self Cites](#)

[CITED JOURNAL DATA](#) [CITING JOURNAL DATA](#) [IMPACT FACTOR TREND](#) [RELATED JOURNALS](#)

Journal Information ⓘ

Full Journal Title: TREES-STRUCTURE AND FUNCTION
 ISO Abbrev. Title: Trees-Struct. Funct.
 JCR Abbrev. Title: TREES-STRUCT FUNCT
 ISSN: 0931-1890
 Issues/Year: 6
 Language: ENGLISH
 Journal Country/Territory: GERMANY
 Publisher: SPRINGER
 Publisher Address: 233 SPRING ST, NEW YORK, NY 10013
 Subject Categories: FORESTRY

[SCOPE NOTE](#) [VIEW JOURNAL SUMMARY LIST](#) [VIEW CATEGORY DATA](#)

Journal Rank in Categories: [JOURNAL RANKING](#)

Eigenfactor® Metrics
 Eigenfactor® Score: 0.00575
 Article Influence® Score: 0.544

Journal Citing Half-Life

The citing half-life for the journal is the median age of the items the journal cited in the current JCR year. Half of the citations in the journal are to items published within the citing half-life.
Citing Half-Life: >10.0 years

Breakdown of the citations *from the journal* by the cumulative percent of 2014 cites to items published in the following years:

Cited Year	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004-all
# Cites from 2014	57	317	431	412	432	407	402	379	356	348	4329
Cumulative %	0.72	4.75	10.23	15.46	20.95	26.12	31.23	36.05	40.57	44.99	100

Citing Half-Life Calculations:

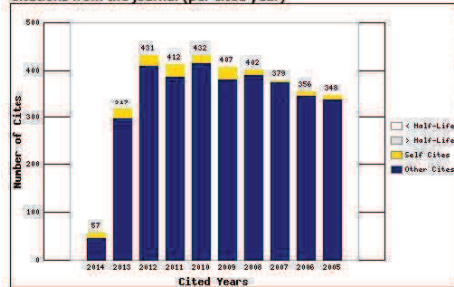
The citing half-life calculation finds the number of publication years from the current JCR year that account for 50% of citations in the journal. Read help for more information on the calculation.

Citing Journal Graph

[Click here for Citing Journal data table.](#)

This graph shows the distribution by cited year of citations from current-year items in the journal TREES-STRUCT FUNCT.

Citations from the journal (per cited year)



- The white/grey division indicates the citing half-life (if < 10.0). Half of the citations from the journal's current items are to items published more recently than the citing half-life.
- The top (gold) portion of each column indicates Journal Self-Citations: citations from items in the journal to items in the same journal.
- The bottom (blue) portion of each column indicates Non-Self Citations: citations from the journal to items in other journals.

Journal Source Data

	Citable items			Other items
	Articles	Reviews	Combined	
Number in JCR year 2014 (A)	151	4	155	3
Number of references (B)	7635	229	7864	6.00
Ratio (B/A)	50.6	57.2	50.7	2.0

Rank in Category: TREES-STRUCTURE AND FUNCTION

Journal Ranking

For 2014, the journal **TREES-STRUCTURE AND FUNCTION** has an Impact Factor of **1.651**.

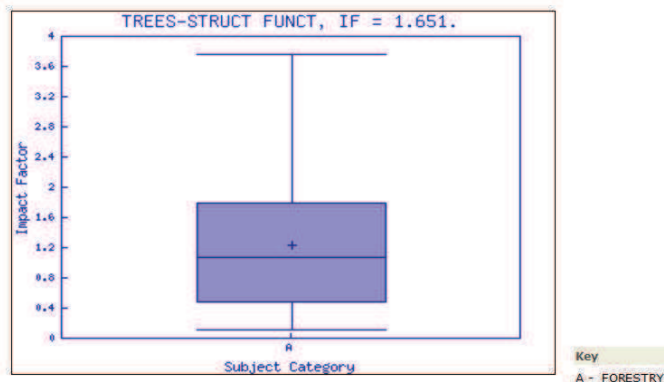
This table shows the ranking of this journal in its subject categories based on Impact Factor.

Category Name	Total Journals in Category	Journal Rank in Category	Quartile in Category
FORESTRY	65	18	Q2

Category Box Plot

For 2014, the journal **TREES-STRUCTURE AND FUNCTION** has an Impact Factor of **1.651**.

This is a box plot of the subject category or categories to which the journal has been assigned. It provides information about the distribution of journals based on Impact Factor values. It shows median, 25th and 75th percentiles, and the extreme values of the distribution.



ANEXO III

SOFTWARE MULRACS

ANEXO III. SOFTWARE MULRACS



MULRACS-Multispectral Radiometric Calibration Software

Tipo: Registro de la propiedad intelectual

Referencia: SA-00/2015/4722

Universidad: Universidad de Salamanca

Códigos UNESCO:

- 2209.18 Fotometría
- 2209.20 Radiometría
- 2209.90 Procesado de Imágenes
- 3311.11 Instrumentos Ópticos

Autores:

- Susana Del Pozo Aguilera
- Mónica Herrero Huerta
- David Hernández López
- Pablo Rodríguez Gonzálvez
- Diego González Aguilera

Resumen:

Aplicación informática para la calibración radiométrica de sensores pasivos en su uso de rango cercano (sin que se vean afectados por la absorción atmosférica de radiación solar). La calibración implementada por dicho software está basada en el método vicario de radiancias y

puede aplicarse tanto al caso de sensores mono-espectrales como multi-espectrales. Una vez el sensor esté calibrado se podrán obtener imágenes geo-referenciadas en magnitudes físicas (reflectancias o radiancias) y diferentes índices de vegetación, las cuales pueden ser explotadas para obtener información sobre recursos naturales, inspecciones naturales,

agricultura de precisión... de gran utilidad para la Comunidad Científica Internacional y empresas privadas que lleven a cabo análisis de imágenes. La figura A muestra la interface del software MULRACS.

Características:

El software MULRACS permite realizar una calibración rigurosa de los sensores a través del método de calibración basado en radiancias. Aplica un ajuste por mínimos cuadrados al nivel digital de las superficies de control recogido por las imágenes capturadas (ecuación 1).

$$Radiancia_i = f(F0_i, F1_i, ND_i) + \Delta\alpha_i \quad (1)$$

donde $F0_i$ (offset) y $F1_i$ (gain) son los parámetros de calibración del sensor, ND_i es el nivel digital de las superficies de control y α_i es un coeficiente de corrección, todos ellos para cada una de las i bandas del sensor.

Como método de resolución iterativo se escoge el Método robusto de mínimos cuadrados Danés que asocia una serie de pesos en función del valor residual de cada iteración. De esta manera se descartan valores atípicos.

Datos de entrada:

- ✓ Superficies artificiales de control lambertianas
- ✓ Curva de respuesta espectral de las superficies de control
- ✓ Eficiencia cuántica del sensor CCD/CMOS y de los filtros del sensor pasivo
- ✓ Imágenes con sus parámetros de captura (focal, ISO, TIEMPO DE EXPOSICION Y APERTURA)

Productos:

- ✓ Parámetros radiométricos por canal
- ✓ Parámetros estadísticos de la calibración
- ✓ Irradiancia solar
- ✓ Imágenes en radiancia
- ✓ Imágenes en reflectancia
- ✓ Imágenes en índices vegetales

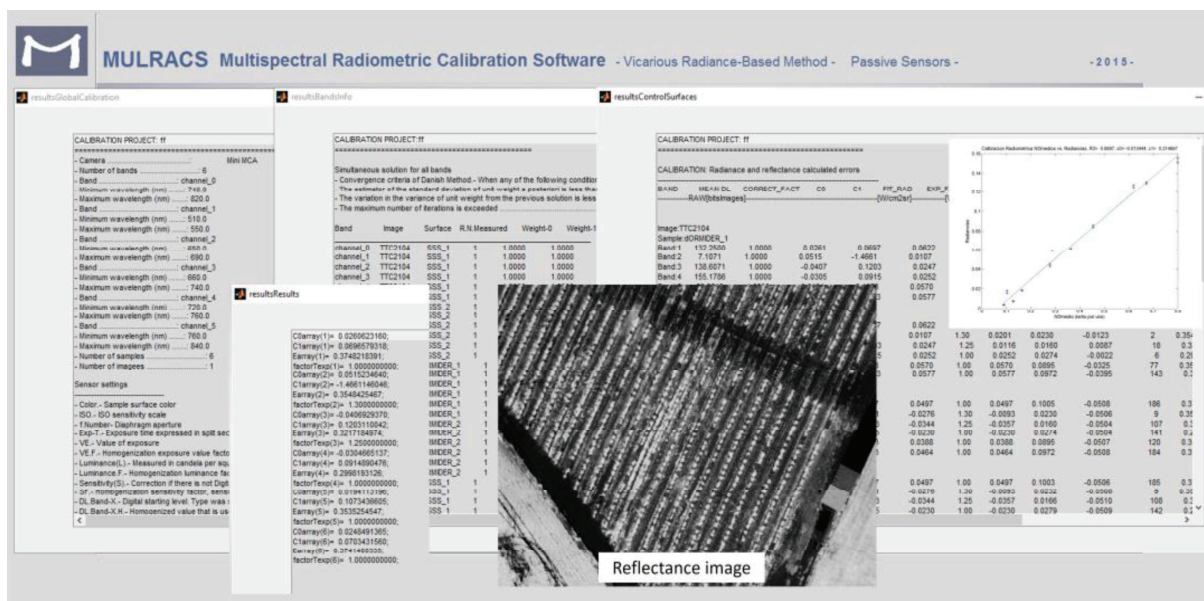


Figure A: Interface de MULRACS

ANEXO IV

MERITOS ADICIONALES

ANEXO IV. MÉRITOS ADICIONALES

1. Beca Cátedra-Iberdrola en colaboración con la Universidad de Salamanca en el grupo TIDOP. 2011-2012

La beca de investigación en el grupo TIDOP, perteneciente al Departamento de Ingeniería Cartográfica y del Terreno de la Universidad Politécnica Superior de Ávila, con Diego González Aguilera como tutor, tuvo una duración de 12 meses. Se centro en el estudio de la Teledetección y Fotogrametría de rango cercano aplicada a la Agricultura de Precisión.

2. Participación en Proyectos: “EnSmart, modelado energético para Smart Cities (ENSmart)”. Universidad de Salamanca. 2013-2014

Plantilla del equipo de investigación del Proyecto Nacional ENSmart, con Diego González Aguilera como investigador principal, durante el año 2013 y 2014 en la Universidad de Salamanca. Se basó en el uso de técnicas de visión computacional, fotogrametría aérea de rango cercano, datos procedentes de Mobile LiDAR System y procesamiento de imágenes térmicas en edificios urbanos para su modelado energético.

3. Participación en Proyectos: “Fusión y Plataforma de Análisis de Nubes de Puntos Geoespaciales, Coberturas y Datos Volumétricos Big Data (IQmulus)”. Universidad Tecnológica de Delft. 2015

Plantilla del equipo de investigación del Proyecto Europeo IQmulus, con Roderik Lindenbergh como investigador principal, durante el año 2015 en la Universidad Tecnológica de Delft. La aportación se basa en la aplicación de datos procedentes de Mobile LiDAR System en la caracterización de árboles urbanos mediante la creación de una plataforma Bigdata.

4. Participación en Proyectos: “Evaluación comparativa internacional sobre métodos procedentes de datos de escáner láser terrestre para el sector forestal”. Instituto de Investigación Geoespacial finlandés (FGI). 2015

Participación en el Proyecto ‘TLS benchmarking 2016’, con Xinlian Liang, Harri Kaartinen y Juha Hyyppä como investigadores principales procedentes del FGI. El objetivo del proyecto es evaluar la calidad, exactitud y viabilidad de métodos automáticos, semiautomáticos o manuales de extracción de árboles basados en datos procedentes del escáner láser terrestre.

5. Participación en Congresos: SilviLaser 2015, ISPRS Geospatial Week. La Grande Motte (France)

Presentación de una metodología para extraer parámetros geométricos del arbolado urbano a través de Mobile LiDAR System en la ISPRS Geospatial Week.

6. Estancia de investigación en el Instituto de Desarrollo Regional de Castilla-La Mancha (España) en el grupo de Teledetección y Sistemas de Información Geográfica. 2014

La estancia de investigación en el Instituto de Desarrollo Regional de Castilla-La Mancha, con David Hernández López como tutor, tuvo una duración de dos meses (01/07/2014-31/08/2014). Se basó en la obtención y análisis de ortofotos multiespectrales y de diferentes índices vegetales sobre un viñedo mediante un sensor de rango cercano embarcado en una plataforma aérea de bajo coste.

7. Estancia de investigación en la Universidad Tecnológica de Delft (Holanda) en el departamento de Geociencia y Teledetección. 2015

La estancia de investigación en la Universidad Tecnológica de Delft, con Roderik Lindenbergh como tutor, tuvo una duración de 5 meses (01/02/2015-30/06/2015). Se basó en el tratamiento de datos procedentes de Mobile LiDAR System para clasificar y segmentar árboles individuales en un contexto urbano, así como en la extracción de parámetros geométricos arbóreos para su aplicación directa en inventarios de arbolado urbano.

8. Publicación de Congreso, ISPRS Geospatial Week 2015: “Automated Large Scale Parameter Extraction of Road-side Trees Sampled by a Laser Mobile Mapping System”. R.C. Lindenbergh, D. Berthold, B. Sirmacek, M. Herrero-Huerta, J. Wang

Este trabajo considera la extracción automatizada a gran escala de parámetros arbóreos a través de Mobile LiDAR System. Las nubes de puntos se procesan consecutivamente mediante un resamplado y posterior clasificación y segmentación en

árboles individuales, permitiendo la obtención de tamaños y ubicaciones. El método se demuestra a lo largo de 7 kilómetros de carretera.

9. Publicación de Congreso, ISPRS Geospatial Week 2015: “Automatic Tree Breast Height Diameter Estimation by Mobile LiDAR System in an Urban Context”. Mónica Herrero-Huerta and Roderik Lindenbergh

Este estudio se centra en el desarrollo de una metodología innovadora para calcular automáticamente el diámetro a la altura del pecho de los árboles urbanos (DBH) a través de Mobile LiDAR System. La calidad de los resultados confirman la viabilidad de la metodología propuesta, proporcionando escalabilidad a un análisis exhaustivo de árboles urbanos.

10.Desarrollo de Software: MULRACS (MULTispecpectral RAdiometric Calibration of passive sensors). Susana Del Pozo-Aguilera, Mónica Herrero-Huerta, David Hernández-López, Pablo Rodríguez-Gonzálvez, Diego González-Aguilera. 2015

Aplicación informática para la calibración radiométrica de sensores pasivos multiespectrales de rango cercano.

11.Desarrollo de Software: ATPE (Automatic Tree Parameter Extraction by mobile LiDAR system). Mónica Herrero-Huerta and Roderik Lindenbergh. 2015

Aplicación informática para la extracción de parámetros geométricos arbóreos a partir de Mobile LiDAR System.